4-30-2018

THE LOCATIONAL PATTERNS AND SOCIOECONOMIC EFFECTS OF THE NEW MARKETS TAX CREDIT AND LOW INCOME HOUSING TAX CREDIT IN DISTRESSED METROPOLITAN CENSUS TRACTS

Michael Henderson

THE LOCATIONAL PATTERNS AND SOCIOECONOMIC EFFECTS OF THE NEW MARKETS TAX CREDIT AND LOW INCOME HOUSING TAX CREDIT IN DISTRESSED METROPOLITAN CENSUS TRACTS

A Dissertation
Presented to
The Academic Faculty

By

Michael Joseph Henderson

In Partial Fulfillment
Of the Requirements for the Degree
Doctor of Philosophy in Public Policy

Georgia State University and
Georgia Institute of Technology

May 2018

THE LOCATIONAL PATTERNS AND SOCIOECONOMIC EFFECTS OF THE NEW MARKETS TAX CREDIT AND LOW INCOME HOUSING TAX CREDIT IN DISTRESSED METROPOLITAN CENSUS TRACTS

Approved by:

Dr. Cathy Yang Liu, Advisor
Andrew Young School of Policy Studies
Georgia State University

Dr. Ann-Margaret Esnard
Andrew Young School of Policy Studies
Georgia State University

Dr. Kimberley Roussin Isett
School of Public Policy
Georgia Institute of Technology

Dr. Jesse D. Lecy
College of Public Service and
Community Solutions
Arizona State University

Dr. Deirdre A. Oakley
College of Arts & Sciences
Georgia State University

Date Approved: December 13, 2017

For Yoko, Mei, and the one we'll meet soon

ACKNOWLEDGEMENTS

I would like to thank Cathy Liu, Jesse Lecy, Ann-Margaret Esnard, Deirdre Oakley, and Kimberley Isett for serving on my dissertation committee and, both individually and as a group, providing the intellectual insight, constant encouragement, and guidance that helped me complete this journey. I am particularly grateful to Cathy and Jesse for both taking the reins as my dissertation advisor along the way.

In addition to my dissertation committee, many other professors and researchers at the Andrew Young School at Georgia State, School of Public Policy at Georgia Tech, and elsewhere made important contributions to my development as a scholar, including Greg Lewis, Christine Roch, Dennis Young, Harvey Newman, Janelle Kerlin, Julia Melkers, John Steward, Naima Wong, Karen Minyard, Beth Fuller, Chris Parker, Glen Landers, Eric Twombly, Kristen Holtz, and Michael Marchioni. I learned important, sometimes difficult lessons from each of you that taught me what it means to be a legit social scientist, so thank you. I am also grateful for the advice, support, and patience of Abena Otudor, Lisa Shepard, Mathieu Arp, Michelle Lacoss, and Jade Charnigo.

Thank you to my fellow students Jonathan Boyd, Karen Cheung, Chris Wyczalkowski, Jason Edwards, Ric Kolenda, Rahul Pathak, Xi Huang, and many others at Georgia State and Georgia Tech, for your camaraderie, and for your intellectual and social support.

Completing my doctoral studies would have been impossible without the anchor that is my family. I cannot express how grateful I am to my parents, Tom and Marcia Henderson, for their constant love and support throughout my life, Jan Henderson for her advice and input on my dissertation, and Keiko Ogawa for making it possible for me to complete my studies.

Most importantly, I thank my wife Yoko, daughter Mei, and the new little one that will be joining our family soon. This is as much your accomplishment as it is mine. I am a truly lucky man to have had you by my side on this long journey.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

SUMMARY

This dissertation investigates the role of two federal place-based programs, the New Markets Tax Credit (NMTC) and Low Income Housing Tax Credit (LIHTC), as tools for revitalizing distressed communities. The first empirical chapter organizes low-income, high-poverty metropolitan census tracts into a typology based on their demographic, class status, built environment, and location characteristics in 2000. Principal components analysis uncovered three prominent neighborhood dimensions: class status, urbanization, and black socioeconomic isolation. These dimensions were entered into a cluster analysis, which identified ten distinct types of poor metropolitan neighborhoods. NMTC investment, LIHTC investment, and socioeconomic ascent were highly correlated across neighborhood types. This finding supports an assumption made in previous studies that developers, who play an important role in determining where subsidized projects are located, are motivated to seek out areas primed to undergo socioeconomic ascent. The neighborhood dimension describing the degree of urbanization was only baseline variable consistently related to both sources of place-based investment and future socioeconomic ascent, suggesting that developer preferences are informed by observable urbanization-related factors. These findings were then applied to the development of a model for estimating the effects of place-based investment on a neighborhood's socioeconomic trajectory. I use a variation of propensity score matching allowing for multiple treatment conditions to compare 2000 to 2010 changes in income, poverty, unemployment, and home values between census tracts that received different combinations of investment through (a) both NMTC and LIHTC, (b) NMTC alone, (c) LIHTC alone, and (d) neither program. Findings revealed that the addition of NMTC had a positive impact on socioeconomic trajectories, while adding LIHTC-subsidized housing into a census tract could have a positive, negligible, or negative impact, depending on the comparison condition. Overall, this dissertation contributes to a better understanding of why certain types of poor places may be more likely to benefit from these types of market-driven place-based initiatives than others, and introduces a more integrated and nuanced approach for evaluating programs that operate within shared geographic space to address different facets of neighborhood poverty.

CHAPTER 1

INTRODUCTION

Cities are spatially organized into areas with varying levels of affluence and poverty. These patterns are important because "the community of which we are a part is both influenced by and influences our individual strengths and weaknesses (Edelman, 2012)." Places that are home to disproportionate numbers of poor people begin to take on the characteristic vulnerabilities of their residents, exacerbating the disadvantages faced by the poor. There are consequences to living in a poor neighborhood even for individuals and families that are not poor (Coutts & Kawachi, 2006), but deleterious environmental conditions overwhelmingly affect those with the fewest protective resources (Galster, 2012; Sampson, 2012). Since 2000, the number of poor communities, and the number of poor people living in low-quality residential environments has increased sharply (P. A. Jargowsky, 2013); thus, the harmful effects of spatially concentrated poverty remain among the foremost social and policy concerns.

As a community-level condition, poverty compounds the cycle of burdens placed on poor individuals and families (Sampson, 2012). Targeting the mechanisms through which the residential environment shapes outcomes is an important part of federal antipoverty strategy, with $82 billion in federal spending dedicated to place-based programs in 2012 alone (Kneebone & Berube, 2013). While there is broad agreement that addressing issues of place is critical to improving the life chances of vulnerable populations, the viability of strategies that specifically target socially and economically distressed places as an effective, efficient, and equitable means of improving the lives of poor people remains a point of debate among academics and experts (Partridge & Rickman, 2006).

1.1 The Debate over Place-based Policies

Poverty is a complex and multifaceted problem, and its harmful effects work their way into the lives of people and communities through multiple levels of influence (Sallis et al., 2006). Policy efforts to address poverty are often designed to intervene at either the individual/family level or at the community level. Policies that treat the individual/family dimensions of poverty are often referred to as "people-based", and those that act at the community level as "place-based." People-based policies that transfer benefits directly to specific individuals or groups include means-tested programs such as the Supplemental Nutrition Assistance Program (SNAP; i.e. food stamps), cash assistance, and the Earned Income Tax Credit (EITC). Also falling into the people-based silo are housing voucher programs, such as the Moving to Opportunity program (de Souza Briggs, Popkin, & Goering, 2010), which address the harmful effects of living in a poor neighborhood by giving poor families the opportunity to move into places that provide better access to quality schools, increased employment opportunities, offer more and better local amenities and services, and are overall less socioeconomically isolating.

In contrast, place-based programs are not designed with the intention of benefitting specific individuals. Instead, they steer resources into places where high numbers or percentages of poor people are located (Partridge & Rickman, 2006). There is an ongoing and unresolved debate regarding the wisdom of place-based strategies. Prominent criticisms include the argument that targeting places is often more expensive than targeting people (Deng, 2005); that low-income places are unable to effectively harness investments and generate positive externalities (Glaeser & Gottlieb, 2008); that tying benefits to specific geographic areas induces poor people to remain in place even if they would be better off moving elsewhere (Kraybill & Kilkenny, 2003) and similarly distorts the location decisions of businesses (Ladd, 1994); and that place-based investments are often siphoned off by a variety of unintended beneficiaries, including investors (Gurley-Calvez, Gilbert, Harper, Marples, & Daly, 2009), landowners, and higher-skilled commuters and new residents (Crane & Manville, 2008; Glaeser & Gottlieb, 2008).

While the debate over the relative strengths and weaknesses of people- and place-based approaches is far from settled (Neumark & Simpson, 2014), considerable theoretical and applied evidence exists to support the notion that intervening at the community level, if done well, can be part of an effective antipoverty strategy. For example, the claim that targeting places for investment distorts residential location decisions (Kraybill & Kilkenny, 2003) assumes a high level of mobility among the populations living in areas typically targeted by place-based policies (Ladd, 1994). The large body of spatial mismatch literature (Gobillon, Selod, & Zenou, 2007) suggests a legitimate use for strategies conducive to local employment growth, particularly in areas populated by low-income, low-skill, or minority workers (Arnott, 1998), given the persistence of barriers including commuting costs, housing affordability, and discrimination.

Place-based policies are also often criticized for wastefulness and inefficiency. Glaeser and Gottlieb (2008) make the case that the strength of place-targeting strategies is undercut by the inability of economically disadvantaged places to leverage investments into sufficient positive externalities for the surrounding area. A related concern is that the resources injected into poor communities do little to help current residents, as benefits are too easily siphoned off by unintended beneficiaries including investors, landowners, higher-skilled commuters, and new residents (Crane & Manville, 2008; Glaeser & Gottlieb, 2008; Gurley-Calvez, Gilbert, Harper, Marples, & Daly, 2009). While both arguments highlight legitimate causes for concern, evidence from a recent evaluation of the place-based Empowerment Zone (EZ) program suggests that neither is a foregone outcome. Busso, Gregory, and Kline (2010) found that the benefits generated by EZ investment into low-income census tracts significantly exceeded costs by raising productivity in the surrounding area, increasing total employment in targeted tracts and generating substantial wage increases for residents.

Targeting the places where poor people live has also been characterized as a more expensive means to an end that could be more efficiently realized by providing resources directly to needy individuals and families. Yet Richter, Sniderman, Klesta, and Manzo (2013) challenge the premise of judging place-based programs solely based on cost-effectiveness, as the benefits generated are often difficult to quantify in simple dollars-per-unit terms. Along the same lines, Davidson (2009) rejects the strict dichotomy of person-versus-place that drives the debate, as the experiences of a local population invariably bleed into facets of place, while upstream social and environmental mechanisms directly impact people. These final two points suggest the need for a more nuanced take on the role of place-based policies.

1.2 Study Overview

Given the overwhelming size and complexity of poverty and its community-level dimensions, the debate over place-based policies is unlikely to be resolved any time soon (Teitz & Chapple, 1998). Still, there are numerous opportunities for moving the discussion forward. This dissertation offers new insights into several underexplored areas of research on place-based policies by investigating investments made into poor neighborhoods during the 2000s through two prominent federal programs, the New Markets Tax Credit (NMTC) and the Low Income Housing Tax Credit (LIHTC).

A lack of access to the financial resources critical to fostering local development activity is one of the root causes of persistent neighborhood poverty (Teitz & Chapple, 1998). Both NMTC and LIHTC address this market failure by providing incentives to investors, businesses, and for-profit and non-profit developers that minimize the risks- both real and perceived- and maximize the potential benefits of investing in socioeconomically distressed areas. Given this shared purpose, NMTC and LIHTC incorporate many of the same policy design elements, target closely overlapping subsets of low-income, high-poverty census tracts, and rely on the participation of similar market actors to achieve core program goals of increased investment in locations and types of development that have suffered from chronic underinvestment.

Though similar in terms of policy design, NMTC and LIHTC are notably different in the types of development activity they support: NMTC is an economic development program that supports new and expanding businesses, as well as a variety of non-residential real estate projects in distressed census tracts (CDFI Fund, 2012), while LIHTC has for the last three decades served as the federal government's most important program for increasing the supply of affordable housing for low-income families (U.S. Department of Housing and Urban Development, 2014).

This dissertation represents the first effort to examine NMTC and LIHTC together within in a single study. This research consists of two empirical chapters focused on the policy design similarities underlying NMTC and LIHTC, as well as the differences in the kinds of development activity each program supports. The first empirical chapter investigates the locational patterns of NMTC and LIHTC investment across different types of poor neighborhoods. The second chapter examines the effects of NMTC and LIHTC investment on neighborhood socioeconomic conditions.

1.2.1 NMTC and LIHTC Locational Patterns

Income and poverty levels in the census tract in which a proposed project is located are the primary factors for determining eligibility for both NMTC and LIHTC. For NMTC, the requirement is that either the poverty rate must be greater than 20 percent, or median family income (MFI) in the census tract must be less than 80 percent of MFI in the surrounding metro area or state, whichever is greater (MFI ratio). While LIHTC can be used in any location, regardless of local socioeconomic conditions, significantly more generous incentives are available for affordable housing placed into census tract with greater than 25 percent poverty or an MFI ratio below 60 percent.

The locations of NMTC- and LIHTC-subsidized projects are not selected at random from the pool of all eligible census tracts. Given their similar policy designs, similar combinations of factors affect the likelihood that an eligible census tract will be targeted for NMTC or LIHTC. These factors include federal provisions that encourage development in locations meeting various additional requirements beyond the basic eligibility criteria described above, the decisions of the entities that administer NMTC and LIHTC in determining which applications for program financing to select, and the location decisions of the developers, businesses, and nonprofits that use these programs as a source of financing.

Understanding the treatment selection process is critical for estimating treatment effects. Unfortunately, several key drivers of NMTC and LIHTC treatment selection are difficult to observe, complicating efforts to develop quasiexperimental studies that can offer convincing causal arguments. In particular, the decision-making process of developers has been identified in previous studies of both NMTC and LIHTC as an important, yet unobservable, determinant of treatment selection. A primary purpose of the first empirical chapter is to better understand what differentiates the minority of census tracts targeted for NMTC and/or LIHTC investment from the majority that meet the relevant eligibility requirements, but that are not selected as locations for subsidized development activity.

I begin the study by using principal components analysis (PCA) to condense the demographic, class status, housing, and location characteristics of low-income, high-poverty metropolitan census tracts in 2000 into a theoretically meaningful set of neighborhood dimensions. These dimensions are then entered into a cluster analysis to organize census tracts into a typology of poor metropolitan neighborhoods in 2000.

This neighborhood typology serves as the basis for examining patterns of socioeconomic change, NMTC investment, and LIHTC investment during the 2000s. In previous evaluations, it has been assumed that the actors responsible for selecting the sites for NMTC- and LIHTC-subsidized projects seek out locations that they expect to perform strongly in the future (Baum-Snow & Marion, 2009; Freedman, 2012; Harger & Ross, 2014). Thus, it is predicted that NMTC and LIHTC investment activity during the 2000s was similarly clustered in the types of poor neighborhoods that possessed combinations of characteristics in 2000 that suggested a strong chance of experiencing socioeconomic ascent by 2010.

This detailed exploration of NMTC and LIHTC locational patterns offers important insights into some of the basic assumptions made about these kinds of market-driven, place-based policies. For one, any neighborhood types where NMTC investment, LIHTC investment, and future socioeconomic ascent all come into alignment are likely to be important for understanding the decision-making process of developers. More specifically, I argue that the neighborhood features that define these neighborhood types represent a strong approximation of the latent construct of market actor preferences.

1.2.2 NMTC and LIHTC Socioeconomic Effects

The second empirical chapter examines the effects of NMTC and LIHTC investment on local socioeconomic conditions. As in earlier studies, I focus on changes in indicators of population and neighborhood well-being in census tracts that received program treatment. The current study breaks new ground, however, because the overlaps between NMTC and LIHTC have never been addressed. The first empirical chapter finds that, as predicted, NMTC and LIHTC resources tend to flow into similar kinds of poor neighborhoods, given similarities in policy structure, administration, and the market-based mechanisms employed to steer investment into eligible locations. Considering these results, failing to account for LIHTC activity in an evaluation of NMTC (and vice versa) raises serious concerns of biased estimates due to omitted variable bias.

This part of the study uses matching techniques to identify suitable comparison groups for three discrete treatment conditions: NMTC investment only, LIHTC investment only, or both NMTC and LIHTC investment. In addition to the traditional no-treatment counterfactual, I also estimate the differences of receiving two different treatment conditions.

1.3 Study Organization

Chapter 2 provides an overview of NMTC and LIHTC policy structures, reviews the extant literature on the socioeconomic effects of NMTC and LIHTC investment in low-income, high-poverty census tracts, and discusses some of the key issues that have haunted past investigations. The empirical work is carried out in Chapter 3 and Chapter 4. Chapter 5 synthesizes the overall findings, discusses the limitations and policy implications of this work, and considers future research directions.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

Until the 1930s, antipoverty efforts that treated poverty as a community-level condition were mainly led by local governments, religious groups, and civic organizations (Von Hoffman, 2012). It took the increasing urbanization of the early 20th century along with the wholesale devastation of the Great Depression for the federal government to become heavily involved. FDR's New Deal saw to it that local efforts to combat the problems of urban poverty received new national attention (Whisenant, 2014); for example, by providing federal funding to support state and local planning activities (Levy, 2009).

Housing policy is one area in which the federal government was especially active. Unfortunately, the housing programs that emerged around this time often contributed to the patterns of social and economic isolation that developed over the course of the 20th century. Though providing new opportunities for millions and being responsible for completely reshaping the composition of urban America, these programs were often explicitly discriminatory. The 1934 Home Owner's Loan Corporation (HOLC) revolutionized the housing market by introducing more favorable loan conditions and opening the possibility of homeownership for the first time to many. Soon after, the Federal Housing Authority (FHA) and GI Bill made homeownership even easier by making the federal government the insurer of millions of home loans and offering attractive interest rates (Greenberg, 1997; Schill & Wachter, 1995). Unfortunately, the structure of these programs ensured that these opportunities were not equally available to all Americans. For example, the FHA would not insure mortgages in poor, racially mixed neighborhoods. As a result, most FHA activity took place in new, racially segregated suburban areas (Gotham, 2000). In conjunction the rapidly changing transportation infrastructure that made the outlying areas surrounding central cities into feasible locations for industry, commerce and housing, these early housing programs provided the fuel for a self-reinforcing process of disinvestment, crime, and other social issues mainly affecting the poor, minority residents of inner city neighborhoods that took hold in the ensuing decades.

Although the 1960s saw an evolution in the federal approach to urban revitalization through the introduction of initiatives like the Model Cities Program, as well as the gains made by the civil rights movement, it was not until the 1970s that policy changes with significant enforcement mechanisms began to take effect. The 1975 Home Mortgage Disclosure Act (HMDA) required lenders to report their lending activities at the census tract level on an annual basis. The result was significantly more accountability, as lenders are now required to make public records on the loans provided to individuals in order to ensure that they are meeting their communities' needs and not engaging in discriminatory lending practices (FFIEC, 2013). Similarly, the 1977 Community Reinvestment Act (CRA) required insured lenders to take steps to ensure that they are meeting the financing needs of their entire service area, including low- and moderate-income communities. Lenders are graded based on the degree to which they satisfy this mandate (Reserve, 2014).

The decision-making process for many New Deal programs represented a top-down approach that allowed little room for the input of the local people most directly impacted by the Depression as well as efforts to improve conditions (Von Hoffman, 2012). In the wake of the shift away from top-down community revitalization policies with few accountability or equity checks came a new group of programs that emphasized both local control over the decision-making process and remedying the damage caused by earlier federal policies. One of the earliest and most well-known of these policies is the Community Development Block Grant (CDBG), a product of the Community Development Act of 1974. CDBGs are given out to municipalities on a formula basis, and leave communities with more discretion over the use of these funds than did earlier federal programs. One significant caveat to this is that the majority of CDBG funds are to be used to benefit low- and moderate-income people (Levy, 2009). NMTC and LIHTC share much of the substance of CDBG; in particular, an emphasis on harnessing the wisdom of local markets into the revitalization process.

2.2 The New Markets Tax Credit

While the United States' history of growth and economic prosperity is the result of a system that provides broad access to capital (Barr, 2002), many lower-income communities have been handicapped by a chronic lack of access to the financial resources critical for creating and supporting economic activity. Inequitable lending practices from the past that prevented the flow of investment into poor places and populations have had significant and long-lasting impacts. The goal of NMTC is to eliminate and compensate for the forces that have left many communities severely underinvested by addressing the persistent perception that poor places represent increased investment and business risk (Abravanel, 2010).

Introduced in the Community Renewal Tax Relief Act of 2000, NMTC is administered by the US Department of the Treasury through the Community Development Financial Institution (CDFI) Fund. The CDFI Fund certifies local financial institutions, known as Community Development Entities (CDEs), to apply for one or more of several tax credit and grant programs, including NMTC. CDEs specialize in providing financial services to traditionally underserved individuals, businesses, and communities. The primary function of NMTC is to increase the flow of private individual and corporate investment into distressed communities. Through 13 rounds of allocations, the CDFI Fund has awarded over $50 billion in tax credit authority to CDEs through NMTC (Fund, 2017b).

NMTC is a competitive program in which certified CDEs apply to the CDFI Fund for the authorization to grant tax credits to investors. In exchange for making an equity investment into a CDE, the investor receives a tax credit valued at 39 percent of the amount invested. The credit is claimed on the investor's federal income taxes over the course of seven years: five percent of the investment amount is credited for each of the first three years, and six percent is credited the remaining four years. Thus, an investment of $1 million would yield $50,000 in tax credits per year in years 1-3 and $60,000 per year in years 4-7. At the end of seven years, the investor receives back the principal investment plus any accrued interest (Black & Caputo, 2013). Investors often view low-income locations as high-risk and low-reward. The tax credit helps to overcome this perception by offering investors a minimum guaranteed return on their investment. CDEs use the capital raised from private and corporate investors to offer financing for projects located in eligible census tracts, typically at more favorable terms than are available through conventional financing sources (Abravanel et al., 2013; CDFI Fund, 2012). A visualization of NMTC structure is shown in Figure 1.

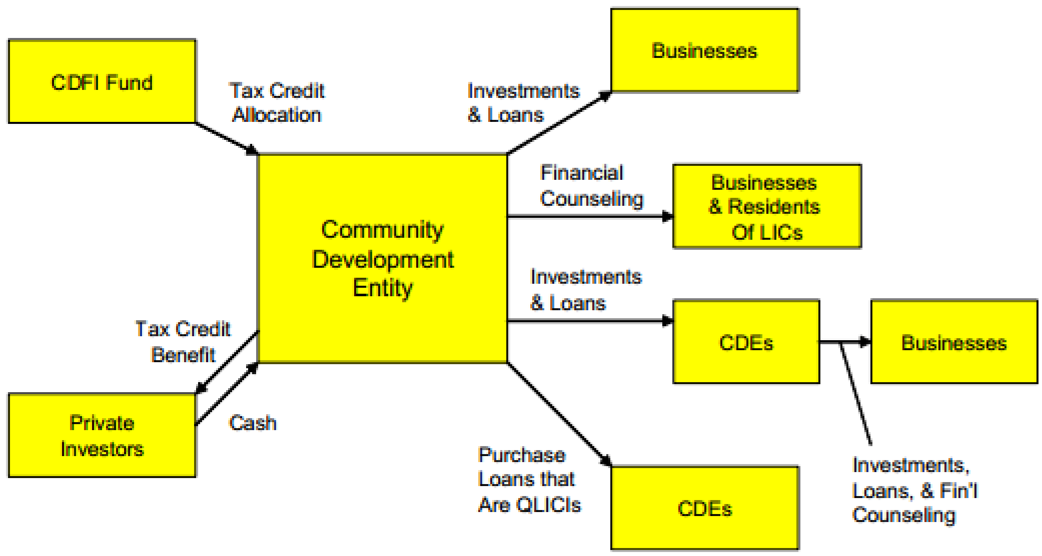

Figure 1. NMTC Structure (IRS, 2010)

As mentioned in Chapter 1, the basic requirements for NMTC eligibility are:

- median family income in the census tract less than 80 percent of income in the greater of the surrounding metropolitan area or state (MFI ratio), or

- poverty rate greater than 20 percent

While any census tract meeting either the MFI ratio or poverty rate threshold is eligible for NMTC, the application for NMTC allocation authority indicates that CDEs are scored more favorably if they commit to making at least 75 percent of investments into businesses or developments located in areas of "severe distress," defined as census tracts with MFI ratio less than 60 percent, poverty rate greater than 30 percent, or unemployment rate at least 1.5 times the national average. CDEs may also be scored more favorably if they commit to adhering to two or more other conditions, such as investing in places that are more distressed than the basic thresholds require, but not sufficiently so to be designated as "severe distress," plus into difficult development areas such as brownfields, FEMA-designated disaster areas, and certain rural areas, or in projects that are owned by low-income persons, or that will primarily employ or serve low-income persons (Fund, 2017a).

2.2.1 Current state of NMTC literature

Evidence that NMTC is an effective tool for overcoming traditional biases against low-income areas is an important benchmark of program success. The perception that poor communities present increased business and investment risk is not unfounded; yet it is also recognized that there are opportunities to be found in such places, given significant unmet market demand (Porter, 1997). The hope is that an initial round of NMTC-incentivized investment will begin to erode traditional biases against underserved communities and make private investors more willing to consider the market opportunities in poor neighborhoods. Limited evidence is beginning to emerge suggesting that NMTC can be an effective catalyst for private investment (Harger & Ross, 2014); however, others have been critical of NMTC for failing to live up to this goal (Forbes, 2006; Swack, Hangen, & Northrup, 2015).

A related concern is that NMTC may be used by investors to subsidize investments that would have been made even in the absence of the program. Using an instrumental variable and propensity score matching approach, Gurley-Calvez, Gilbert, Harper, Marples, & Daly (2009) examined data from the CDFI Fund and the IRS to determine the effect of NMTC on individual and corporate investment behavior between 2000 and 2004. The authors found that the introduction of NMTC as an investment opportunity in 2003 had a significant impact on the behavior of individual investors, as the differences in investment activity between individual investors and a comparison group in 2000 was significantly smaller than it was in 2004, by which time there was opportunity to invest in NMTC. On the other hand, there was no significant difference in the change between corporate NMTC investors and a comparison group over the same time period. These mixed findings are attributed to two primary factors. First, individuals are more likely to use NMTC as an opportunity to invest in distressed communities to fulfill social or ethical goals. Second, there are already mechanisms in place for inducing corporate investors to invest in distressed and underserved places.

Evaluations have also focused on the degree to which NMTC-subsidized projects are relevant to the needs and capacities of the local population. As long as a for-profit or non-profit entity can demonstrate that a substantial amount of its activity takes place within an eligible census tract, there are relatively few formal restrictions placed on the specific kinds of activities that would disqualify it from being classified as a qualified active low-income business (QALICB), and thus eligible for NMTC financing (IRS, 2010). Some have argued that this lack of oversight sometimes leads to the use of NMTC for projects that do little to benefit local residents (Bokath, 2010). However, evaluations have generally found that in this respect, program provisions have been effective at decreasing the risk of NMTC being used for projects incompatible with program goals or local needs. For example, a survey of CDEs found a strong emphasis on supporting projects likely to benefit lower-income populations, such as manufacturing, education, and healthcare facilities (NMTCC, 2012). That demand for tax credit allocation authority by CDEs greatly outstrips the supply of funds further alleviates this concern; high demand combined with a competitive application process that takes into consideration potential community impact has the effect of filtering out projects not in the spirit of NMTC (Abravanel et al., 2013). On the other hand, Brostek (2009) found that between 2005 and 2008, even after controlling for other relevant factors, minority-owned CDEs were rated lower by the CDFI Fund during the competitive application process and were less likely to receive tax credit allocation authority.

2.3 The Low Income Housing Tax Credit

LIHTC was introduced in the Tax Reform Act of 1986, and has since grown to become the federal government's most important mechanism for creating new affordable rental housing for low-income families (Cummings & DiPasquale, 1999). As of 2012, LIHTC has helped finance the construction and rehabilitation of over 2.5 million affordable housing units (Erickson, Galloway, & Cytron, 2012).

Like NMTC, LIHTC is a federal program housed within the Department of the Treasury. However, LIHTC is primarily administered at the state level, as funding is allocated annually by the IRS to each state's housing credit agency (HCA) on a per-capita basis. In 1986, the allocation was $1.25 per state resident. This was later increased to $1.75 per resident, and as of 2003, the allocation adjusts annually to account for inflation (U.S. Department of Housing and Urban Development, 2014).

To receive LIHTC financing, a housing developer applies for tax credits to support a specific development to the HCA of the state in which the development is located. The developer then sells the tax credits to private investors in exchange for the purchase of an equity stake in the development. The credit is applied to the investor's income tax liability over the next ten years, and the equity investment is used to finance the completion of the housing development project (Desai, Dharmapala, & Singhal, 2008). Figure 2 provides a visualization of the LIHTC policy structure.

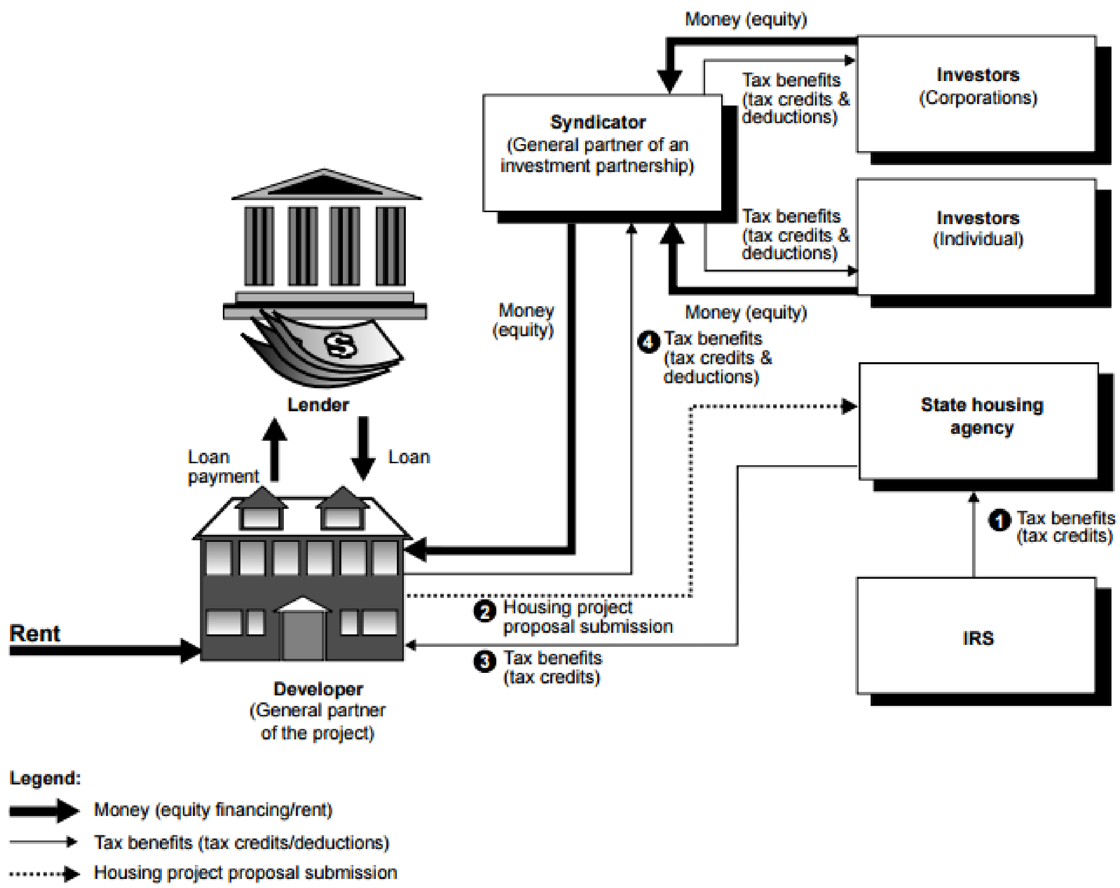

Figure 2: LIHTC structure (White, 1997)

LIHTC is not a straightforward place-based policy in the same sense as NMTC, as affordable housing development in any location is eligible for LIHTC, regardless of local economic conditions. Instead of a strict location-based requirement, LIHTC developments must be occupied by a minimum number of low-income people. Specifically, at least 20 percent of renters must earn less than half of the area median gross income (AMI), or at least 40 percent of renters must earn less than 60 percent of AMI (U.S. Department of Housing and Urban Development, 2014).

In practice, however, LIHTC has clear place-based implications due to a provision that awards an additional 30 percent in tax credits for affordable housing units placed into Qualified Census Tracts (QCTs). The designation of a census tract as a QCT is based on the same two indicators of local economic distress used to determine NMTC eligibility. However, the thresholds required for QCT status are stricter. To be designated a QCT, either the MFI ratio must be less than 60 percent (versus 80 percent for NMTC), or the poverty rate must be greater than 25 percent (versus 20 percent for NMTC).

2.4 NMTC and LIHTC Socioeconomic Effects

When NMTC was first introduced by Congress in 2000, the stated intent for the new program was that it would "result in the creation of jobs and material improvement in the lives of residents of low-income communities (IRS, 2010)." Insufficient access to economic opportunity is widely recognized as one of the root causes of concentrated poverty (Galster, 2012; Teitz & Chapple, 1998; Wilson, 2011). Thus, the ultimate sign of NMTC success would come from evidence that the economic development activity it supports has a meaningful positive impact on the socioeconomic well-being of local residents.

To date, only one study has specifically examined the effects of NMTC investment on community conditions. Freedman (2012) used a regression discontinuity design to compare the differences in socioeconomic trajectories from 2000 to 2010 of census tracts that were barely eligible for NMTC to those that were barely ineligible, on the basis of the MFI ratio requirement. Freedman found that census tracts on the eligible side of the 80 percent threshold experienced significant improvements in poverty rates and unemployment rates compared to otherwise similar census tracts on the ineligible side of the threshold. On the other hand, there were no significant differences in home value growth, income growth, or housing turnover.

The role of LIHTC as a tool for revitalizing distressed neighborhoods has received considerably more attention. In particular, the provision of LIHTC that provides additional tax credits for housing placed into QCTs has been a source of focus, and even controversy. By providing an additional incentive for developers to create housing exclusively for poor families into neighborhoods that are already disproportionately poor, LIHTC on the surface appears to contradict the last thirty years of federal housing policy by reinforcing existing patterns of concentrated poverty. HUD's HOPE VI program was introduced in 1992 for the purpose of deconcentrating poverty through the replacement of substandard public housing developments, which were typically located in low-income areas and only housed low-income families, with mixed-income developments (Popkin, 2004). Since then, a number of other federal efforts, such as the Empowerment Zone program (Forbes, 2006; Oakley & Tsao, 2007), Moving to Opportunity (de Souza Briggs et al., 2010), and Choice Neighborhoods (Wilson, 2010) have also focused on tackling the problems of concentrated poverty.

The reality is more complex, however, as LIHTC-subsidized development activity in low-income areas may generate positive spillovers in the surrounding area and help foster further revitalization (Ellen, O'Regan, & Voicu, 2009). If an LIHTC-subsidized development upgrades existing low-quality housing or develops parcels of vacant and abandoned land, these improvements may outweigh the poverty-concentrating effects of new low-income housing units (Baum-Snow & Marion, 2009). In addition, the federal provisions of LIHTC were updated in 2000 to require states to give preference to housing projects that are integrated into a larger community revitalization plan. While some states have taken this requirement seriously, others appear to only pay it lip service in developing state-level guidelines for allocating LIHTC resources (Johnson, 2014); nevertheless, this more holistic approach to the siting of LIHTC developments within low-income areas would appear to ease at least some of the conflict between LIHTC and the federal government's current goals in housing and antipoverty policy.

Whether the positive spillovers of new development and the preference for projects taking place within the context of a community revitalization plan outweigh the potential for LIHTC to reinforce patterns of concentrated poverty has not been definitively established in the literature. In a study of the interaction between LIHTC and the Housing Choice Voucher (HCV) program, which allows low-income households to secure housing in lower-poverty areas by subsidizing their rent in market-rate units, Williamson, Smith, & Strambi-Kramer (2009) found that HCVs in Florida did not subsidize rent enough to allow the lowest-income households to find affordable housing within the private market. As a result, HCVs were disproportionately used by the very poorest families to secure housing in LIHTC units located in QCTs. Thus, the siting of LIHTC units in low-income areas may reinforce the tendency for families receiving housing vouchers to choose locations that are relatively poor (Galvez, 2010), particularly if poor households use LIHTC to supplement subsidies received through other housing programs. On the other hand, Horn & O'Regan (2011) found no evidence that LIHTC locational patterns lead to increased racial segregation, an issue that is intrinsically tied to patterns of economic isolation (Massey, 1993; Sampson & Wilson, 1995; Wilson, 2012).

If there is any conclusion to be drawn from the extant literature on LIHTC, it is that the local socioeconomic context, including the level of economic distress and preexisting socioeconomic trends, in large part determine whether LIHTC-subsidized development is likely to have a positive or negative impact on community conditions. In one of the few national-level studies to date, Baum-Snow and Marion (2009) found that from 1990 to 2000, the neighborhood effects of LIHTC investment depended on whether a LIHTC development was placed into a gentrifying, stable, or declining neighborhood. When placed into "gentrifying" census tracts, in which property values increased from 1980 to 1990, LIHTC developments led to increased household turnover and declines in income. On the other hand, when placed into stable or declining areas, LIHTC had a positive impact on property values.

2.5 Research Challenges

2.5.1 Unobserved drivers of site selection

Previous evaluations of NMTC and LIHTC have been plagued by at least two methodological issues. The first is that the drivers of site selection in NMTC and LIHTC are not well understood. However, an important takeaway from the extant literature is that there are different kinds of poor places. Census tracts eligible for NMTC and LIHTC vary by the severity of socioeconomic distress, recent socioeconomic trajectory, location-both regionally and within a particular metropolitan area, and in many other ways. Understanding these differences may hold the key to understanding why some eligible locations may be more likely targets for place-based investment than others, and for those places that are targeted, both the degree and direction of socioeconomic change that the investment is likely to produce.

Because current federal initiatives address market failures by embracing market forces, theory and evidence suggest that the locational patterns of place-based investment are driven in part on the expectations of market actors about the current and future economic viability of low-income neighborhoods. Therefore, place-based investment may be disproportionately concentrated in poor places that, at least in the eyes of developers, are relatively well-positioned to experience socioeconomic ascent.

It is unlikely that NMTC and LIHTC developers are indifferent between potential project locations. An evaluation of NMTC by Abravanel et al. (2013) found that most of the businesses that had received program financing owned the property for an approved project prior to making the decision to apply for NMTC. As taking ownership of a property typically precedes the decision to apply for NMTC, this finding suggests that the neighborhoods into which NMTC-subsidized projects are placed must possess certain advantages that overcome the traditional bias against economically distressed places. There is also some evidence that the locational patterns of LIHTC activity are influenced by gravitational forces that favor some neighborhoods over others. Specifically, Eriksen et al. (2007) found that LIHTC-subsidized housing development tends to be located in areas where large amounts of unsubsidized housing development activity would be expected.

Though there is some evidence available to help inform the preference structures of developers, the specific neighborhood factors that influence site selection have not been explored in depth for either NMTC or LIHTC. Thus, a limitation noted in previous studies examining the effects of program treatment on neighborhood socioeconomic trajectories is the possibility of model misspecification due to unobserved developer preferences for certain kinds of poor places (Baum-Snow & Marion, 2009; Ellen et al., 2009; Freedman, 2012). Concern over this potential source of bias is downplayed by the argument that if comparison tracts are similar to treated ones on observed baseline characteristics, then they are most likely similar on unobserved factors as well. Unfortunately, this assumption is impossible to verify, because there is no direct method for determining the similarity of observations on variables that are not measured.

Overall, little has been done to examine developers' locational preferences as drivers of NMTC or LIHTC site selection. Similarly, little has been done to specify the structure of the relationship between unobserved determinants of project location and the observable neighborhood characteristics typically assumed to serve as appropriate proxies for developer preferences. This is a problem because even a small amount of model misspecification can lead to biased estimates of program impact, particularly if the misspecification is tied to particularly influential variables (Ho, Imai, King, & Stuart, 2007).

Previous evaluations of both NMTC (Freedman, 2012) and LIHTC (Baum-Snow & Marion, 2009) have circumvented this selection issue through the adoption of regression discontinuity (RD) designs. RD is a promising approach for evaluating programs like NMTC and LIHTC where eligibility is based on relatively strict and clearly defined thresholds. Given the extreme unlikelihood of nonrandom sorting of census tracts around either program's poverty or income eligibility thresholds, there is a strong case to be made that the only systematic difference between the groups of census tracts falling just on either side of an eligibility threshold is eligibility status itself. Thus, any observed differences in the socioeconomic changes experienced by census tracts that were barely eligible for NMTC or LIHTC, and those that were barely ineligible should be attributable to the effects of program treatment.

The internal validity of a well-designed RD study approaches that of a true randomized experiment (Trochim & Donnelly, 2001). However, this strength comes at a price. First, RD only allows for estimating the effects of treatment on the entire group of eligible census tracts, rather than on those that actually received NMTC or LIHTC treatment. Second, valid comparisons can only be made between census tracts falling within a tight band on either side of the eligibility threshold. Consequently, the findings from a study of NMTC or LIHTC using RD are only generalizable to a small subset of moderately distressed eligible places, and cannot offer insight into the effects of program treatment on the much larger number of more severely distressed census tracts.

If the underlying processes that drive NMTC and LIHTC site selection were better understood, comparison groups that more closely resemble targeted census tracts on all important pretreatment attributes could be identified. This would generate new opportunities for investigating the effects of NMTC and LIHTC on community conditions using quasiexperimental methods that avoid the inherent limitations of RD.

To understand how NMTC and LIHTC site selection occurs, it is necessary to first understand the nature of the problem these and other place-based programs are designed to address. Thus, the first empirical chapter of the dissertation begins with a more fundamental question: what are the different types of low-income, high-poverty census tracts? Identifying the drivers of differentiation among the places eligible for NMTC and LIHTC may yield important clues about how site selection occurs through these sorts of market-driven initiatives. Both NMTC and LIHTC site selection are assumed to be a function of multiple neighborhood-level considerations. Are the neighborhood factors that predict NMTC investment the same as those that predict LIHTC? Or, are the location decisions for each program made through independent and unrelated processes?

2.5.2 Implications of NMTC and LIHTC parallels for evaluation

The second problem haunting evaluations of these programs is the potential for estimates of program impact of one program to be biased by failing to account for the presence of the other program in the same or similar types of distressed census tracts. This omitted variable bias issue is closely related to the treatment selection issue discussed in the previous section, yet to my knowledge it has never been acknowledged or studied. It is important at this point to reiterate just how similar NMTC and LIHTC are to one another, in terms of overall policy structure and rules, the actors involved, and the mechanisms employed through which resources are delivered into low-income, high-poverty census tracts.

First, NMTC and LIHTC define important aspects of program eligibility based on similar thresholds of income and poverty. However, the basic requirements for NMTC eligibility are less strict than the corresponding thresholds used to determine whether a developer is eligible for a more generous level of tax credit through LIHTC; thus, every census tract that is eligible for NMTC is necessarily eligible for additional tax credits through LIHTC. There are also additional NMTC provisions that give preference to eligible places that meet additional standards of distress. These high distress areas resemble the LIHTC requirements even more closely than the basic NMTC requirements.

The overlapping tiers of NMTC and LIHTC eligibility would not be of concern from a causal validity standpoint if the processes that determined NMTC and LIHTC treatment selection were unrelated. This is unlikely, however, given that previous studies, which have only looked at NMTC and LIHTC individually, arrive at basically identical conclusions about the unobserved drivers of site selection. In both programs developers are assumed to seek out distressed areas that they perceive to be on an upward socioeconomic trajectory

To summarize, the locational choices available to developers utilizing NMTC and LIHTC resources are bounded by program rules to closely overlapping sets of low-income, high-poverty census tracts. Within this shared space, theory and limited empirical evidence suggests that NMTC and LIHTC development activity gravitates towards similar kinds of distressed places through unobserved processes related to the preferences of developers.

The deep parallels linking NMTC and LIHTC are consequential for the development of valid research designs. The basic goal in a causal study of a program like NMTC or LIHTC is to draw comparisons between two groups of census tracts that, aside from one group having received the given program treatment, were identical in all other meaningful respects. This requirement is violated if the factors that determine a census tract's probability of receiving NMTC treatment and LIHTC treatment are highly correlated.

While omitted variable bias is a concern whether the omitted variable pushes estimates of program impact up or down, the unresolved controversy surrounding the LIHTC provision that incentivizes developers to favor areas that are already disproportionately poor when considering potential locations for affordable housing creation adds an interesting layer to the complex relationship between NMTC and LIHTC. To the degree that LIHTC investment does concentrate poverty and drive the socioeconomic trajectories of targeted census tracts downwards, there is the distinct possibility that any evidence pointing to the effectiveness of NMTC as a tool for revitalizing distressed neighborhoods would be eroded, or even cancelled out, by the unaccounted-for presence of LIHTC in similar kinds of census tracts. By extension then, failing to account for the revitalizing effects of NMTC activity in an evaluation focused on LIHTC could result in an underestimation of the poverty-concentrating effects of LIHTC.

CHAPTER 3

NEIGHBORHOOD TYPES AND PLACE-BASED INVESTMENT PATTERNS

3.1 Introduction

This is the first of two empirical chapters in this dissertation. In it I investigate the ways in which a poor neighborhood's starting point explains its future socioeconomic trajectory, its likelihood of being targeted for different kinds of place-based investment, and the underlying relationship between these processes. As discussed in the previous chapter, scholars looking at NMTC and LIHTC suggest that, given the market-driven nature of these programs, development activity gravitates towards areas that are primed to experience socioeconomic ascent. Unfortunately, the links between the unobserved drivers of site selection and observable neighborhood characteristics that are plausibly related have not been thoroughly investigated for either NMTC or LIHTC. The uncertainty around NMTC and LIHTC treatment selection processes presents a methodological roadblock that has limited efforts to evaluate these programs.

In general, the idea that developers and similar market actors seek out areas that they think will improve over time is uncontroversial. On the other hand, one of the strongest predictors of future poverty is past poverty (Peters, 2009). Thus, most of the census tracts that are eligible for NMTC or LIHTC investment at a given time will remain poor going forward. The justification for programs like NMTC and LIHTC, which restrict eligibility to benefit from public resources to subsets of high-income, low-poverty census tracts, is that the market has failed to provide such places with adequate access to the financial resources needed to support economic growth. How do developers discern between potential project locations when their options are limited almost entirely to places that (a) have been chronically ignored by market forces, and (b) are in most cases unlikely to experience significant ascent?

Though most neighborhoods remain roughly the same over time, some are revitalized, and still others fall deeper into the vicious cycle of concentrated poverty. For the poor neighborhoods that do improve, what are the available and most likely pathways of ascent? From the developer perspective, are some ascending neighborhoods more attractive locations for place-based investment than others? Similarly, are there subsets of stable or declining poor neighborhoods that nevertheless appeal to developers for reasons unrelated to their socioeconomic trajectory?

Finally, NMTC and LIHTC have never been examined together as they are in this study. Despite this, scholars looking at each program individually have arrived at similar conclusions about how observed investment patterns are produced. This is no surprise, given their numerous structural similarities as instruments for delivering resources into distressed census tracts. On the other hand, NMTC and LIHTC are still distinct programs that operate independently of one another. Furthermore, they focus on distinct types of development activity, and it may not be the case that the neighborhood factors most relevant to the economic and community development goals of NMTC are identical to the local considerations most important for the siting of affordable housing development through LIHTC. Are the locational patterns of NMTC investment and LIHTC investment explained by similar neighborhood-level considerations? Because patterns of investment, particularly in the context of developer preferences, have not been examined in detail for either NMTC or LIHTC, it is difficult to speculate about whether, how, or to what degree NMTC and LIHTC site selection might be related.

To explore these questions, I develop a typology of distressed metropolitan census tracts that, given levels of income and poverty in 2000, would have been eligible for NMTC, and in most cases eligible for additional tax credits through LIHTC, in the ensuing years. Typologies are an important tools in neighborhood research because they provide a framework for revealing the underlying structures and key features of complex urban landscapes. The goal here is to classify distressed census tracts in such a way that there are plausible theoretical and common-sense explanations for the links between the initial attributes and subsequent socioeconomic trajectories of each neighborhood type. These explanations can then serve as a reference point for better understanding the observed patterns of NMTC investment and LIHTC investment during the 2000s, given the argument that developers are motivated to seek out the poor neighborhoods most likely to follow an upward socioeconomic trajectory.

3.2 Developing a Neighborhood Typology

Starting with the pioneering Chicago school sociologists, urban scholars have been working to understand how cities are structured and how they change from an ecological perspective since the early 20th century. Thus, though there is no universal definition for what defines a neighborhood, there is broad agreement that neighborhoods are complex entities consisting of an intricately related mix of people, place, interactions, shared norms, and perceived or physical symbolic elements (Schwirian, 1983). Furthermore, neighborhoods exist within, and changes to them are largely driven by enduring upstream economic, religious, political, cultural, and geographic contexts (Galea, Freudenberg, & Vlahov, 2006).

Galster (2001) lays these foundational neighborhood elements out in more detail. He defines neighborhood as "the bundle of spatially based attributes associated with clusters of residences, sometimes in conjunction with other land uses," and drawing from an expansive body of literature, identifies ten types of neighborhood attributes. Individually, each attribute type shines a light on one part of the larger neighborhood structure. Combined, they provide a comprehensive overall view of that structure. Once spatial boundaries are established, a neighborhood can be described in terms of:

- The structural characteristics of the buildings
- Infrastructure characteristics
- Population demographics
- Population class status
- Public services and amenities associated with the tax base
- Environmental characteristics, such as pollution and geographic features
- Relative location of the neighborhood/proximity to employment and commercial areas
- The strength and organization of the local political network
- Social-interactive characteristics (e.g. social capital, cohesion)
- Sentimental characteristics (e.g. place-attachment, residents' self-identification with neighborhood, historic buildings)

The composition, quality, and presence of each attribute can vary widely from one neighborhood to the next. In this multi-dimensional context, every neighborhood is in a sense unique. However, it would be all but impossible, and potentially unhelpful, to incorporate elements of all ten neighborhood attributes into a single typology. Depending on the purpose of the classification, some attributes are more relevant than others for conceptualizing neighborhoods. For example, housing market typologies are an increasingly popular tool among policymakers for making strategic investment decisions

(Boswell, 2011; Goldstein, 2012; Reid, 2011). In many cases, housing market typologies classify neighborhoods according to features of the built environment alone, and do not include any indicators describing local populations (Boswell, 2011). In contrast, typologies that are more descriptive and exploratory in nature, such as several recent efforts to reveal the full extent of suburban diversity (Hanlon, 2009; Mikelbank, 2004; Orfield, 2011), take a more comprehensive and holistic tack by incorporating numerous indicators describing the population, the built environment, infrastructure, and location.

Scholars looking at NMTC and LIHTC have for the most part been vague in identifying specific neighborhood attributes that developers are likely to pay attention to when making location decisions. Similarly, there are no a priori claims made in this study that any specific neighborhood attributes, either individually or in concert, bear particular relevance to a poor neighborhood's socioeconomic trajectory. This chapter is motivated by the general hypothesis that a neighborhood's socioeconomic trajectory is a function of its initial attributes, leaving open the possibility that the specific combination of attributes driving socioeconomic change may vary by neighborhood context. To minimize the risk of missing any key aspects of neighborhood change, it is therefore important in this study to conceptualize neighborhoods in as broad and comprehensive a manner as possible.

Obtaining appropriate indicators to represent the types of neighborhood attributes identified by Galster is an unavoidable limiting factor for developing a comprehensive neighborhood typology. The availability and quality of relevant data points varies considerably by city, county, and metro area. However, in national studies, census data is the only viable source for relevant and universally available neighborhood indicators. Thus, neighborhoods are most commonly operationalized as census tracts in urban research. The tract-level variables available through the census are most closely related to the following four types of neighborhood attributes: (a) the structural characteristics of the buildings, and more specifically local housing characteristics; (b) demographic characteristics of the resident population; (c) class status characteristics of the resident population; and (d) the relative location of the census tract within the metropolitan area.

3.2.1 Proximity/relative location

The imbalance in living conditions in the city versus the suburbs is a fundamental source of tension that urban theory has long used to explain the organization of cities and the outward momentum of urban growth. For example, the invasion-succession hypothesis (Burgess, 2008) carries with it the implication that residential segregation along the lines of race, ethnicity, and class is a part of this tension, and is furthermore a relatively enduring feature of the urban landscape. However, it also assumes that minority groups, once sufficient economic progress has been made, do have the ability to upgrade their residential environment by relocating to more desirable areas.

This assumption broke down in the post-WWII years, as residential mobility for minority groups eroded due to a combination of improving transportation infrastructure, the corresponding spatial reorganization of employment areas that diminished the importance of living near the city center, and housing policies and practices that were often explicitly discriminatory.

In the last few decades, the nature of the relationship between poverty and place has continued to shift and evolve. Notably, the simple dichotomy of inner city deprivation and suburban prosperity has come under increased scrutiny. During the 1990s, neighborhoods that experienced socioeconomic ascent were concentrated in the inner cities and outermost suburbs of metropolitan areas (Kingsley, 2007). Unfortunately, the growing challenges facing older, inner-ring suburbs have been overshadowed by both the prosperity and rapid growth of newer suburban areas and the continuing problems in much of the inner city, leaving the first suburbs “caught in a policy blindspot (Puentes & Orfield, 2002).” Since 2000, the dispersion of neighborhood poverty throughout metropolitan areas has continued (P. A. Jargowsky, 2013).

Several recent typologies have worked to overcome the popular narrative of suburban stability and homogeneity by revealing the true diversity of suburbs. For example, Mikelbank applied hierarchical cluster analysis to a set of population, economic, and government variables (Mikelbank, 2004) on a sample of non-central-city metropolitan places, which revealed 10 distinct types of suburban cities. He found that fewer than half of suburban cities were classified into groups that possessed the attributes traditionally associated with suburbs. Narrowing the focus further, Hanlon discovered significant variation in the types of inner-ring suburbs in terms of race, class, and ethnicity (Hanlon, 2009).

3.2.2 Population Demographics

Taken at face value, the concept of neighborhood poverty implies only some degree of economic segregation. However, it is as much an issue of racial and ethnic isolation as one of class and economics. Though there is debate as to whether the persistent inequities in the life chances of minority populations trapped in low-quality residential environments are driven primarily by economic factors (Wilson, 1978) or are fundamentally rooted in racism (Massey & Denton, 1993), the importance of incorporating aspects of race and ethnicity into a typology focused on neighborhood poverty would be difficult to understate.

Despite the association of economic and racial segregation as nearly synonymous issues, there is in reality wide variation in the demographic composition of poor neighborhoods. Though still disproportionately affecting minority populations, since 2000, the number of poor whites living in high poverty neighborhoods has increased more than any other group (P. A. Jargowsky, 2013). More generally, in any metropolitan area there are bound to be pockets of poverty in which different populations are most prominent. There is likely to be a strong degree of regional variation in the kinds of poor neighborhoods that exist along the lines of race and ethnicity (Delmelle, 2017).

Recent research on gentrification suggests that the demographic profile of a poor neighborhood may affect its chances of undergoing socioeconomic ascent. Specifically, the presence of Asians in a poor neighborhood has been found to be positively associated with gentrification (Hwang, 2016), while black and Hispanic neighborhoods are more likely to experience socioeconomic stability or decline (Hwang & Sampson, 2014).

3.2.3 Population Class Status

While almost all neighborhoods have some degree of poverty, determining the point at which the struggles of poor residents become a feature of the neighborhood itself is not straightforward. The Census Bureau defines poverty areas as census tracts with greater than 20 percent poverty ("Poverty Areas," 1995). Though many studies of neighborhood poverty follow this official definition, others have operationalized neighborhood poverty at 30 percent (Cortright & Mahmoudi, 2014), while Jargowsky and

Bane found, after touring neighborhoods with various poverty rates throughout the US, that a 40 percent threshold may more closely reflect the tipping point beyond which the concentration effects of poverty become visible neighborhood features (1991). Still others have proposed multidimensional indices of neighborhood distress that incorporate indicators of the urban underclass in addition to poverty status (Kasarda, 1993; Ricketts & Sawhill, 1988).

The various thresholds chosen in past studies illustrate that there are gradients of neighborhood poverty and distress. Though some scholars have focused on neighborhood poverty within a relatively narrow range, more often, all places that meet some minimum requirement are included in the analysis. This approach is bound to cast a wide net, capturing places contending with vastly different levels of deprivation. The class-related characteristics of the resident population have implications for a neighborhood's socioeconomic trajectory. For example, the process of externally-driven gentrification is a rare occurrence in deeply impoverished neighborhoods (Clay, 1979; Helms, 2003). Similarly, ascent through incumbent upgrading is most likely in relatively stable, moderate-income areas (Clay, 1979; Owens, 2012; Van Criekingen & Decroly, 2003). Local income levels also relate to the organizational capacity of the local population in terms of the ability to effectively communicate local needs to government leaders and other decision-makers (Jun & Musso, 2013).

3.2.4 Housing Characteristics

The qualities of the local housing stock can reveal much about a neighborhood, including its function within the metropolitan ecosystem, its needs and assets, its residential population, and its propensity to experience different trajectories of socioeconomic change. For instance, the type of housing that predominates- single family homes versus townhomes, apartments, and other multi-unit structures, provides a rough indicator of where a neighborhood lies along the urban-rural continuum. Owner-occupied housing relates to neighborhood stability, as residential turnover is generally less frequent for homeowners versus renters (Coulton, 2014). It may also lend insight into the physical condition of the housing stock, as owner-occupied housing tends to receive more regular and substantive upkeep than rental housing (Rohe & Stewart, 1996).

In many cities, local housing market conditions may also play a part in determining the kinds of policy interventions that are applied to a poor neighborhood, or even whether a neighborhood is likely to be targeted for public investment at all. Given the reality of limited resources available to address often widespread problems, local governments have in recent years looked to housing market typologies to make strategic decisions for targeting investments into certain areas (Boswell, 2011). The indicators selected to represent local housing markets vary from city to city. In some cases, variables relating to population characteristics are used alongside housing variables, while other cities focus only on facets of the built environment and household structure (*Baltimore City's 2014 Housing Market Typology*, 2015; Goldstein, 2011; Reid, 2011).

3.3 Study Area

The primary study area consists of census tracts that met at least one of the basic NMTC eligibility requirements in 2000: (a) tract MFI less than 80 percent of metro/state MFI; or (b) poverty rate above 20 percent. Any census tract that met one of these requirements but not the other was only included in the study if it was more distressed than the metropolitan average on the non-qualifying indicator. Thus, a relatively small number of "high poverty-high income" and "low poverty-low income" census tracts were excluded even though they were technically sufficiently poor to qualify for NMTC, and potentially for additional tax credits through LIHTC as well. They were excluded because further investigation revealed that these places tended to be poor for reasons that have little to do with the purpose of programs like NMTC and LIHTC, and in ways that set them apart from most distressed places. To illustrate, high-poverty census tracts (>20%) in which the MFI was greater than the MFI of the surrounding metro area were almost exclusively located in well-known college towns (e.g. Ann Arbor), suggesting areas with high concentrations of student housing. Though recent research suggests that poverty, food insecurity, and homelessness are hidden and underreported problems on many college campuses (Goldrick-Rab, Richardson, & Hernandez, 2017), in general, poverty for college students is a planned situation with predefined start- and end-dates. Furthermore, the annual housing churn that occurs as incoming freshmen replace graduating seniors means that poverty rates in neighborhoods with lots of student housing are stable and enduring neighborhood features. In other words, the flavor of poverty in these areas, both at the individual- and neighborhood-level is very different than the structural disadvantages of socioeconomic isolation found in most poor places.

Census tracts with zero or near zero populations, as well as those that had missing values for any of the variables needed to construct the outcome measures were also excluded. Finally, only metropolitan areas that received investment through either NMTC or LIHTC during the treatment period for this study of 2003-2007 were considered. What remained after these exclusions were 14,750 census tracts located within 276 metropolitan areas.

The basic NMTC poverty and income requirements, which are less strict than the corresponding LIHTC thresholds for receiving more generous tax incentives, served as the starting point for identifying the study population. The reasoning for taking this relatively relaxed approach to operationalizing neighborhood poverty was that it would allow for an investigation of place-based investment across the full spectrum of places typically targeted by these types of programs, from the moderately distressed to the extremely impoverished.

However, after working with the data for a time, it became clear that this definition may have been too broad with respect to properly investigating the role of the market actors that use NMTC and LIHTC financing, and specifically their presumed preference for places they believe will experience future socioeconomic ascent, in shaping NMTC and LIHTC investment patterns. Though every census tract included in the primary analysis was eligible for NMTC and LIHTC investment during the 2000s, both programs include provisions favoring census tracts that meet higher criteria of socioeconomic distress than the basic program eligibility requirements dictate. First, as just mentioned, LIHTC requirements for additional tax credits are stricter than the basic NMTC requirements on both the MFI ratio (80 percent for NMTC versus 60 percent for LIHTC) and poverty rate (20 percent for NMTC versus 25 percent for LIHTC) thresholds. Thus, Second, CDEs are more likely to be awarded NMTC allocation authority if they indicate on the program application that at least 75 percent of allocations will go to projects located in eligible census tracts that meet additional requirements (MFI ratio of 60 percent; poverty rate above 30 percent; or unemployment 1.5 times the metropolitan average).

These provisions effectively divide the study population into multiple tiers of eligibility or favorability. If a developer wants to locate a subsidized project into a census tract that is only moderately distressed, they must weigh this preference against the additional benefits they may be able to receive if they instead select a more severely distressed area. In contrast, in more severely distressed census tracts for which all additional rules and provisions have been satisfied, no such competing motivations exist. Thus, the observed locational patterns of NMTC and LIHTC investment in these areas may be a more pure reflection of the preference structures of developers for neighborhoods with certain attributes, rather than other factors affecting site selection.

Thus, I determined that it was important to also investigate the locational patterns of NMTC and LIHTC investment in a subset of "severely distressed" census tracts in which there were no obvious drivers of site selection other than the preferences of developers. For the purpose of this study, a census tract was considered to be severely distressed if it met both of the following conditions: (a) poverty rate above 25 percent, and (b) MFI ratio less than 60 percent. All 5,161 census tracts that met both requirements would have been given the full consideration and benefit of both programs during the 2000s. Descriptive statistics for the primary study population and for the subset of severely distressed census tracts are provided in Table 1.

Table 1. Census Tract Characteristics

	All tracts (n = 14750)	severely distressed tracts (n = 5161)
Year 2000 Attributes *(% unless noted)*		
Poverty Rate	25.86	35.99
MFI Ratio *(tract/metro income)*	59.57	44.85
Unemployment	10.91	14.92
White	35.74	19.20
Black	31.45	45.93
Hispanic	26.66	29.56
Asian	4.41	3.78
Foreign-born	19.28	19.76
High school or less	63.77	70.46
Bachelors or more	13.05	9.41
Vacancy rate	9.37	11.31
Housing owner-occupied	43.85	33.53
Pop.density *(mi^2)*	11567	14928
Density ratio *(tract/metro)*	165	194
Housing in multi-unit structure	45.03	53.31
tract/metro home prices	66.03	57.96
2000 to 2009-2013 SES change *(percentage point, except for median home value change)*		
poverty.ch	4.47	2.75
mfi.ch	-2576	-968
mfi.ratio.ch	-0.75	0.89
unemp.ch	4.58	3.92
mhmval.ch	$44,023	$50,128
Investment from 2003-2007		
NMTC	$5,873,617,231	$3,379,389,616
LIHTC	$1,293,313,586	$734,952,443

3.4 Data

3.4.1 Neighborhood Variables

Variables describing the initial attributes of census tracts came from the 2000 Decennial Census. Variable selection was made with respect to two principal concerns. It was important to include variables relating to the four neighborhood attributes discussed earlier- population demographics, population class status, housing characteristics, and location characteristics- while simultaneously ensuring that the selected variables as a group met the minimum established guidelines and rules of thumb for the methods employed to develop the typology. In particular, the success of factor analysis at reducing a set of observed variables into a smaller number of meaningful and theoretically relevant combined variables depends on how the included variables are related. In general, the aim is to strike a balance between uniqueness and multicollinearity. After experimentation with numerous alternative specifications, the thirteen variables listed in Table 2 were selected to represent neighborhoods.

Table 2. Variables Used to Identify Neighborhood Dimensions

Variable Name	Description
Demographic	
black.pct.00	Percent Black
other.race.pct.00	Percent neither non-Hispanic black nor white
hh_female_kids.pct.00	Percent Female-headed Households
Class Status	
poverty.pct.00	Poverty Rate (%)
mfi.ratio.00	MFI Ratio (tract/metro income)
unemp.pct.00	Unemployment Rate (%)
female_labor.pct.00	Percent of Females 16 and Over in Labor Force
hs.edu.pct.00	Percent of Adults Over 24 with HS Education or Less
Housing	

vac.pct.00	Percent of Housing Units Vacant
multi.pct.00	Percent of Housing Units in Multi-unit Structures
own.pct.00	Percent of Housing Owner-occupied
mhmval.00	Median Home Value
Proximity	
density.00.ratio	Ratio of density in census tract to metro

Most of the indicators used here have found use in previous neighborhood typologies and are generally self-explanatory. Still, a couple comments are necessary. First, the location and proximity characteristics of census tracts are operationalized as the ratio of population density in the census tract to the surrounding metro area. The census tracts included in this study come from a wide range of metropolitan contexts in terms of size and urbanization. This relative measure makes it possible to draw parallels between census tracts that may bear very little surface resemblance, but that occupy the same ecological niche within their respective metropolitan settings. This measure may also do a better job of reflecting proximity characteristics in polycentric urban areas than would a measure that assumes a single central business district, such as distance from downtown.

Second, the percent of females in the labor force was included as an indicator of population class status. It was chosen instead of labor force participation for the entire adult population because from the earliest stages of social area analysis, female labor force participation has been considered an important aspect of family structure, which is one of the fundamental dimensions of social organization in neighborhoods (Greer, 1962; Schwirian, 1983).

Four socioeconomic change indicators were constructed using the 2000 census data and the 2009-2013 American Community Survey (ACS). The outcomes examined in this study are the 2000 to 2009-2013 differences in poverty rate, unemployment rate, median family income, and median home value. The poverty and unemployment measures are percentage point changes. Median family income and median home values measures are inflation-adjusted dollar changes. Together, these four measures provide a well-rounded picture of the socioeconomic trajectory of a census tract during the 2000s.

3.4.2 Program Variables

NMTC and LIHTC data came from each program's respective public data release. The CDFI Fund, which administers NMTC, requires all CDEs that are awarded an NMTC allocation to submit an annual report describing how the allocation was used (Fund, 2017b). Although LIHTC is administered by the IRS, data on LIHTC investment activity is maintained by the US Department of Housing and Urban Development (U.S. Department of Housing and Urban Development, 2014).

The variables describing NMTC and LIHTC investment most relevant to this study are allocation year, the census tract in which the investment occurred, and the dollar amount of the investment. In this chapter, both NMTC investment and LIHTC investment are defined in simple binary terms: a census tract is considered to have received NMTC or LIHTC if there was at least one recorded instance of investment from 2003 to 2007. Three treatment variables were created to indicate whether a census tract received both NMTC and LIHTC, NMTC (irrespective of LIHTC investment, and LIHTC (irrespective of NMTC).

3.5 Method

The approach to typology development applied in this study is well-established in the history of urban research (Shevky & Bell, 1955), and finds continued use today (Hanlon, 2009; Owens, 2012). It is a two-step process. First, the thirteen neighborhood attribute variables shown in Table 2 were entered into a principal components analysis (PCA) to uncover key neighborhood dimensions. Second, cluster analysis was used to delineate distinct subgroups of census tracts based on similar combinations of values along those dimensions.

3.5.1 Principal Components Analysis

A commonly used factor extraction technique in exploratory studies (Pett, Lackey, & Sullivan, 2003), PCA was used to uncover the latent drivers of differentiation among poor census tracts. PCA converts the correlation matrix of a set of variables into uncorrelated linear combinations of those variables, referred to as components. The variables with higher loadings on a component explain more of the variance within that component. The basic idea behind PCA is that the set of variables that load highly against a component may each be describing different facets of some common underlying construct (Field, 2009). In terms of the current study, if the subgroup of observed neighborhood indicators that are strongly associated with a particular component fit together in a theoretical sense, then the relationships between these variables may be pointing towards some unobserved, but meaningful neighborhood dimension.

The *R* package *psych* was used to conduct the PCA. The output of the procedure includes standardized component scores for each census tract on the retained components. A component score is a weighted average of the variables that make up a component; in effect, it is an index of the neighborhood dimension that component represents. Thus, a census tract's component scores describe the nature and strength of its association with the neighborhood dimensions identified by the PCA.

3.5.2 Cluster analysis

Cluster analysis is a computationally intensive procedure, which can be a problem when the goal is to classify a large number of observations. The benefit of PCA in this study is that it summarizes thirteen theoretically relevant neighborhood indicators in a few combined variables. By conducting cluster analysis on these combined variables, much more information about poor neighborhoods can be taken into consideration for identifying neighborhood types than would be possible if individual observed variables were used instead.

The two most common clustering techniques for neighborhood classification in previous studies are hierarchical clustering and clustering through partitioning (e.g., k-means). For example, Mikelbank (2004) used a hierarchical approach to classify the types of suburban places, while Owens (2012) used k-means clustering to examine the various pathways of socioeconomic ascent for different types of census tracts. Both hierarchical and k-means clustering have been subject to criticism for their reliance on heuristics to determine the number and orientation of clusters (Fraley & Raftery, 1998). In this study, a model-based technique was used that incorporates elements of both methods, but takes such decisions out of the hands of user. Instead, the data itself is allowed determine the number and orientation of clusters, as well as the best cluster solution.

The *R* package *mclust* was used to perform the cluster analysis (Fraley & Raftery, 2006). *Mclust* requires the user to specify a range of possible cluster solutions that should be considered. Starting with the highest number in the specified range, *mclust* runs 14 different clustering algorithms, each of which produces clusters with a different combination of geometric attributes in terms of their shape, volume, and orientation.

The program then calculates the Bayesian Information Criterion (BIC) for each alternative cluster solution. The BIC is a model selection tool based on the maximum-likelihood function. Given that the best fitting model is, by definition, the one that places each observation into its own cluster, maximum-likelihood prefers solutions with more clusters. The BIC applies a penalty term to the likelihood to reduce the risk of selecting overly-complex cluster solutions. In general, the best cluster solution is the one with the lowest BIC. In the current study, the 14 clustering algorithms were run for between one and fifteen clusters. Thus, the procedure generated approximately 210 distinct neighborhood classifications, from which the one with the lowest BIC could be selected. The key features and theoretical underpinning of the neighborhood types identified by the preferred cluster solution were then investigated.

3.5.3 Patterns of investment and SES change by neighborhood type

The study then shifts focus to explore the relationships between NMTC investment, LIHTC investment, and socioeconomic change within and across neighborhood types. The measures of NMTC investment, LIHTC investment, and socioeconomic change described earlier were aggregated for each neighborhood type. Place-based investment intensity was operationalized through three variables: the percent of census tracts in each neighborhood type that between 2003 and 2007 received investment through (a) NMTC (regardless of LIHTC investment), (b) LIHTC (regardless of NMTC investment), and (c) both NMTC and LIHTC. Four aggregate measures of socioeconomic change were calculated as well. These were the average of 2000 to 2009-2013 change in (a) MFI, (b) poverty rate, (d) unemployment rate, and (e) median home value.

3.6 Results

3.6.1 Uncovering Neighborhood Dimensions

As mentioned above, the thirteen variables chosen to represent census tracts' initial attributes were selected with respect to their theoretical relevance as well as their ability as a group to satisfy the established guidelines for conducting PCA (Field, 2009). The Kaiser-Meyer Olkin test verified the sampling adequacy of the data, with a value of .74, indicating the suitability of the data as 'good' for conducting PCA. Furthermore, the minimum KMO value for any of the variables was .64, well above the minimum suggested value of .5. Bartlett's test of sphericity found that there was sufficient correlation between all variables to conduct a PCA, while the determinant of the correlation matrix, at .00067, was well above the minimum value of .000001, ruling out concern over multicollinearity.

A common rule of thumb is to retain all components with eigenvalues greater than one, as they have at least as much explanatory power as one of the observed variables. Initial analysis of the data revealed eight components that met this criterion. However, the inflection point on the scree plot in Figure 3 supported retention of only the first three components, as each subsequent component explained relatively little additional model variance. To determine whether eight components, three components, or some number in between provided the most theoretically coherent explanation of the data, several models were run, in which different numbers of components were retained. The oblique rotation *oblimin*, which allows the rotated components to be correlated, was applied.

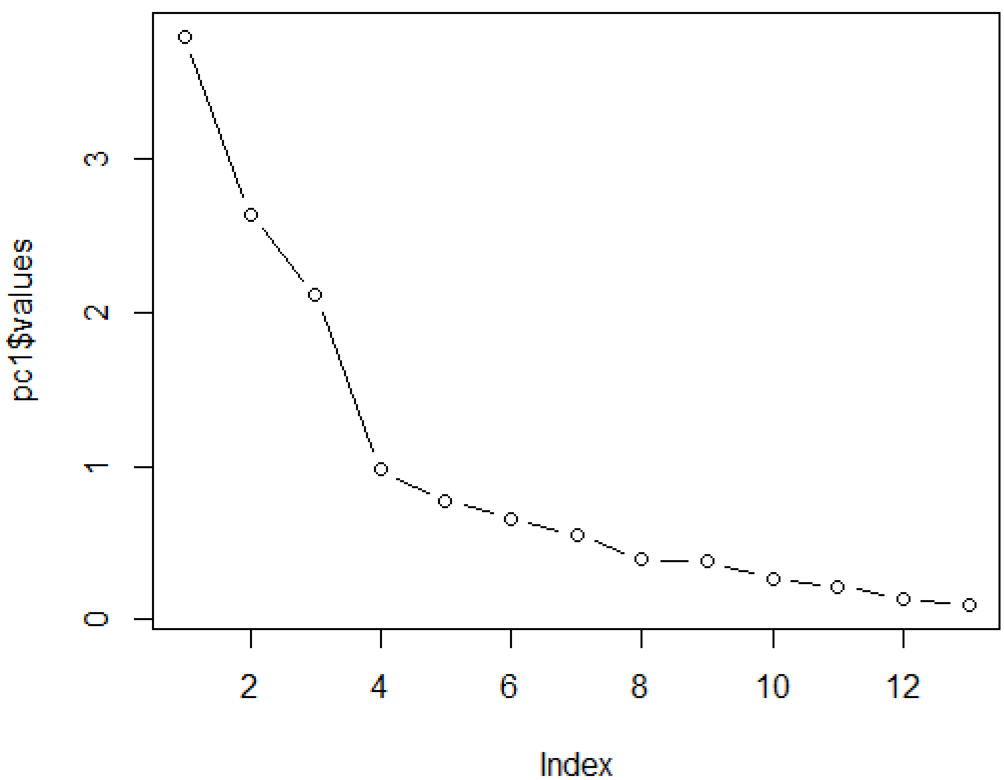

Figure 3: Scree Plot of Component Eigenvalues

The solution retaining three components was determined to provide the best representation of key neighborhood dimensions. Additional components either loaded highly on a single variable, or drew relatively weak connections between two or more variables with no obvious interpretation as meaningful neighborhood dimensions. The three retained components together explained 66 percent of the variance of the original variables. With eigenvalues ranging from 2.82 to 2.89, each of the combined variables had nearly the same explanatory power as three of the original variables. Table 3 shows the loading of each variable on the retained components.

Table 3. Component Loadings

	TC1	TC2	TC3
hs.pct.00	**0.84**	-0.31	-0.08
female_labor.pct.00	**-0.78**	0.14	0.24
poverty.pct.00	**0.62**	0.34	0.31
mfi.ratio.00	**-0.59**	**-0.44**	-0.3
unemp.pct.00	**0.56**	0.18	0.36
own.pct.00	-0.02	**-0.94**	0.02
homes_multi_unit.pct.00	-0.14	**0.91**	-0.07
density.00.ratio	-0.07	**0.57**	0.02
mhmval.00.ratio	-0.39	**0.42**	-0.32
black.pct.00	0.02	-0.05	**0.89**
other.race.00	**0.45**	0.21	**-0.8**
hh_female_kids.pct.00	0.24	0.22	**0.79**
homes_vacant.pct.00	0.18	-0.22	**0.52**

The first neighborhood dimension is primarily an index of population class status and neighborhood distress. It considers the local population's economic strengths and vulnerabilities in shaping the overall wellbeing of the neighborhood. It indicates that poorly educated populations are disconnected from the local labor market, and furthermore that these issues of human capital and social organization are associated with low levels of neighborhood economic wellbeing, in terms of poverty, income, and employment. Interestingly, *other.race.00*, representing the percentage of the population that is neither non-Hispanic black nor non-Hispanic white, also loads against this component in a positive direction, indicating that this neighborhood dimension may in part describe resident socioeconomic distress in poor neighborhoods for reasons unrelated to the well-documented discrimination and isolation of the African American community. Regardless of the demographic composition of the resident population, census tracts with higher values on this dimension are likely to be struggling with more severe socioeconomic distress than the average poor census tract.

The second neighborhood dimension is an urbanization index. It describes the degree to which the composition of the housing stock resembles the typical high-density urban neighborhood where most families rent and much of the housing stock consists of apartments and other multi-unit structures. It also describes the population density of a census tract relative to the metropolitan area in which it is situated. Thus, one would expect the census tracts with the highest positive values on this dimension to be located in the urban core, while those with high negative values to occupy the metropolitan fringe.

The third neighborhood dimension describes the demographic characteristics of the resident population. Specifically though, it is an index of black socioeconomic isolation, as indicated by the opposite loadings for *black.pct.00* and *other.race.00*. Although the percent white variable was not included in the PCA, preliminary analysis suggests that if it had been, it would have contrasted with *black.pct.00* in much the same way. It represents the ugly reality that concentrated poverty is a problem that continues to disproportionately affect the African American community. Compounding the geographic isolation of poor black populations are high rates of home vacancy and a high percentage of single-parent households headed by females.

The results of the PCA were encouraging, as the three retained components appear to represent meaningful neighborhood dimensions. Furthermore, each component corresponds to one of the neighborhood attribute types described by Galster, which served as the guide for variable selection in this study. The first dimension is most strongly associated with the five class status variables. In addition to three of the four housing variables, the second dimension is also described by the relative population density variable, which was used to represent proximity characteristics. The dimension of black socioeconomic isolation includes the three demographic indicators plus one variable describing the qualities of the local housing stock.

3.6.2 Neighborhood Classification

The BIC values of the alternative clustering algorithms for solutions from one to fifteen clusters are displayed in Figure 4. The procedure found that a ten-cluster solution based on an algorithm producing ellipsoidal clusters of varying shape, volume, and orientation (VVV) produced the best model fit.

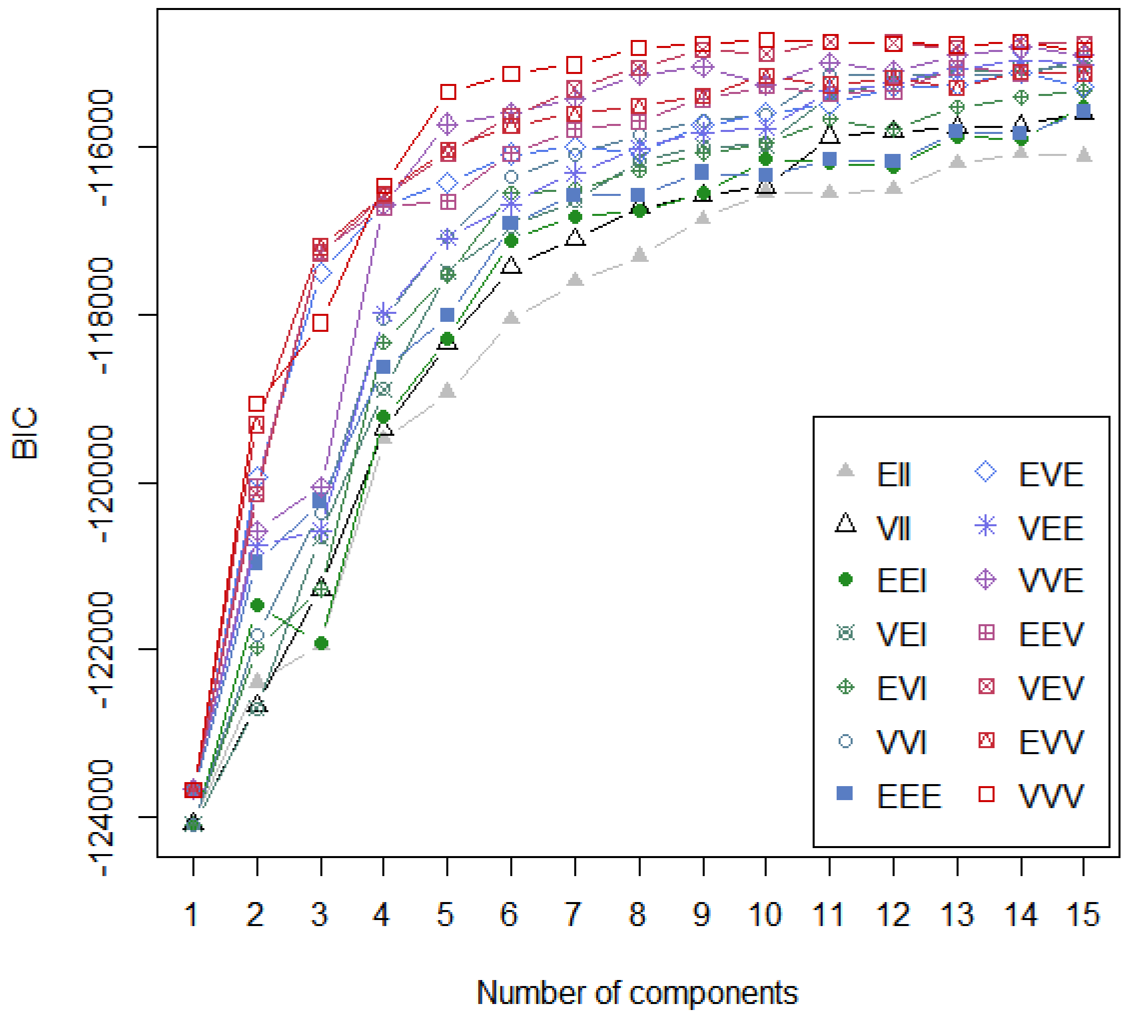

Figure 4: Bayesian Information Criterion Values for Alternative Cluster Solutions

On the other hand, the authors of the *mclust* package, who also developed the model-based approach to clustering it employs, suggest that a parameterization with fewer clusters may be preferable to the solution with the absolute highest BIC if it forms a decisive local maximum (Fraley & Raftery, 1998). While the VVV algorithm forms both a local and global maximum at ten clusters, the amount of additional information gained from adding more clusters drops off sharply beyond five clusters, relative to the cost of additional model complexity. Thus, it was necessary to further examine the content of the alternative model specifications to determine which cluster solution provided the best representation of the types of poor neighborhoods.

While the preliminary analysis of the alternative model specifications is not presented here, in the end I selected the ten-cluster solution. A couple considerations motivated this decision. First, I found that the degree and manner in which NMTC investment, LIHTC investment, and socioeconomic change related to one another within and across neighborhood types was quite consistent as additional clusters were added, up to and including the ten-cluster solution. The nature of these enduring linkages is discussed in depth later in this chapter.

Second, whereas the five-cluster solution grouped census tracts into relatively broad neighborhood archetypes, the more complex specification allowed for a more nuanced examination of underlying relationships between socioeconomic change and place-based investment patterns. To illustrate, the ten-cluster solution identified multiple neighborhood types that experienced socioeconomic ascent from 2000 to 2009-2013. While gentrification commonly serves as a blanket term to describe positive economic gains in poor neighborhoods, scholars recognize it is just one potential pathway of socioeconomic ascent. Other pathways of ascent, notably marginal gentrification, upgrading, and incumbent upgrading, may be partially or entirely distinct from traditional notions of gentrification (Owens, 2012; Van Criekingen & Decroly, 2003). It is also recognized that conditions can deteriorate in a neighborhood for more than one reason. Though socioeconomic trajectories leading to little change over time have received less attention, it stands to reason that there are multiple pathways of stability as well. Comparing the intensity of NMTC and LIHTC activity in poor neighborhoods that were characterized by different combinations of attributes in 2000, but that followed similar socioeconomic trajectories over the course of the 2000s, may allow for a more detailed understanding of the underlying neighborhood-level drivers of place-based investment.

Table 4 provides the group means for the initial attributes and socioeconomic changes of each cluster, as well as the percentage of census tracts in each cluster that received investment through NMTC, LIHTC, or both programs. Though the neighborhood types identified by cluster analysis have no inherent order, I organized them in ascending order of relative population density.

Table 4. Census Tract Characteristics

Cluster	1	2	3	4	5	6	7	8	9	10
n	1073	1259	469	2688	1770	2520	1420	1588	1361	602
Year 2000 attributes *(% unless noted)*										
Total population (mil)	4.1	5.7	1.7	10.9	5.9	9.5	4.5	6.2	5.8	2.2
Poverty rate	17.38	25.74	23.95	17.64	29.36	24.07	37.21	37.09	24.74	22.67
MFI ratio *(tract/metro)*	73.65	64.65	61.61	71.47	54.37	60.56	43.37	43.46	55.05	71.22
Unemployment	6.86	11.22	10.15	7.02	14.23	9.67	17.18	16.01	9.43	5.97
White	71.52	13.52	48.80	57.21	10.22	44.09	14.23	21.50	25.56	63.85
Black	12.24	2.98	37.37	12.77	86.46	32.02	76.87	24.18	4.56	12.66
Hispanic	12.69	78.00	10.73	22.58	2.31	18.05	6.69	46.97	54.53	13.02
Asian	1.09	4.10	1.71	5.33	0.47	3.89	1.40	4.90	13.29	8.38
Recent immigrants	2.72	14.73	3.97	8.58	1.02	8.16	3.79	13.29	25.25	10.89
Foreign-born	6.47	37.74	8.29	17.40	2.29	16.01	7.73	27.29	51.25	17.86
High school diploma or less	67.10	77.21	69.26	56.31	66.80	58.75	67.24	74.24	66.12	29.65
Bachelors or more	9.12	6.01	8.37	15.99	8.51	15.67	10.01	7.64	15.76	43.11
Females in labor force	50.67	44.94	52.05	56.89	52.81	55.93	52.48	44.80	48.06	66.61
Work in management position	20.69	14.81	18.01	24.65	18.69	23.54	20.10	16.22	21.77	42.11
Vacancy rate	11.53	5.80	11.15	6.74	13.69	10.00	14.13	9.83	4.57	6.32
Housing owner-occupied	76.39	58.94	58.23	50.05	56.12	39.04	29.06	27.59	23.95	22.24
Population density (mi^2)	1185	7311	4277	6630	6380	10087	12420	20642	32941	13863
Pop. density ratio *(tract/metro)*	36.05	117.59	121.33	141.36	158.42	182.30	198.85	205.03	225.85	262.72
Homes in multi-unit structures	6.81	19.16	21.59	40.32	23.96	52.99	62.32	61.59	77.70	76.80
Home value ratio *(tract/metro)*	0.61	0.64	0.54	0.72	0.47	0.67	0.58	0.60	0.86	1.02
2000 to 2009-2013 SES change										
Poverty *(percentage point)*	4.14	2.64	7.16	5.72	6.65	6.10	3.41	1.89	1.27	4.49

Table 4 (continued)

MFI *($)*	-2390	-3094	-5691	-4219	-6025	-3185	-793	-771	-126	6126
MFI ratio	1.18	-1.22	-4.44	-2.42	-4.42	-1.70	1.30	0.36	0.72	10.82
Unemployment *(percentage point)*	6.31	2.45	6.89	5.40	8.18	4.99	4.46	1.32	2.04	2.88
Median home value *($)*	13031	35449	12827	35185	7637	38185	46302	60936	131832	63865
2003-2007 investment										
NMTC and LIHTC	0.19	0.48	0.43	0.63	0.34	1.23	1.48	2.46	1.10	1.16
NMTC	2.14	3.42	3.84	3.46	3.73	6.23	7.39	9.26	5.22	6.31
LIHTC	3.63	9.21	8.32	8.33	10.34	10.83	17.04	17.00	7.94	7.64

3.6.3 Types of Poor Neighborhoods

This section discusses the initial attributes, subsequent socioeconomic trajectories, and the intensity of place-based investment for each neighborhood type. Also provided are a series of tables and maps. The tables show the ten large metro areas that had the highest percentage of poor census tracts of each type in 2000[1]. The maps show the distribution of each neighborhood type in metropolitan Atlanta, which was one of seven metro areas that had at least one census tract from each neighborhood type.

[1] Though this study includes census tracts from 276 metropolitan areas, these rankings only consider the 50 largest metro areas by population in 2000. Many of the smaller metro areas had only one or two census tracts in the analysis; thus, they tended to dominate the rankings for each neighborhood type, without providing any useful insight about neighborhood type.

3.6.3.1 Cluster 1: stable white exurbs

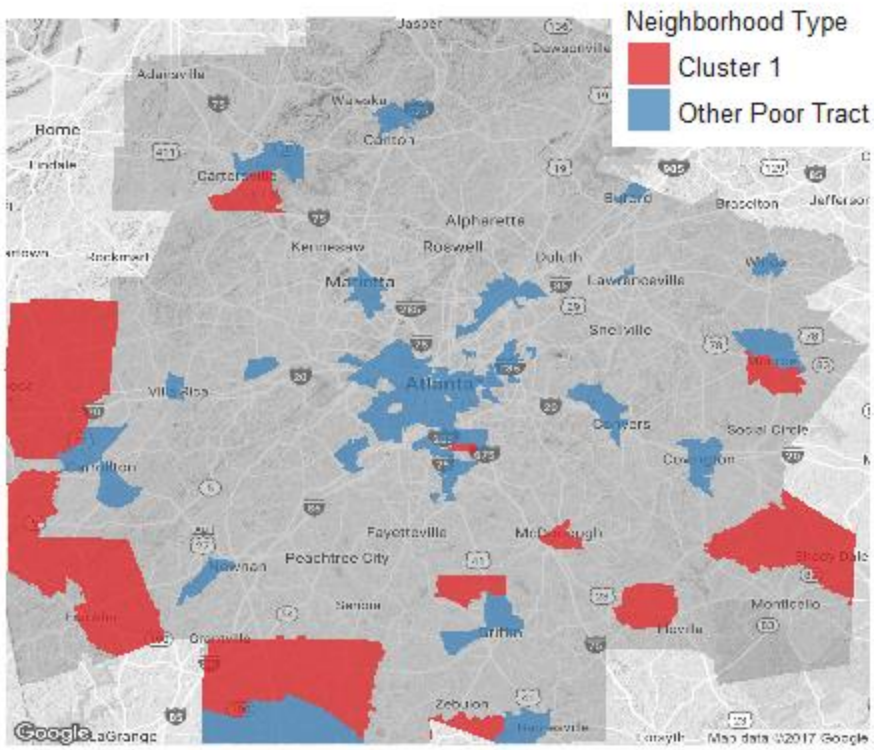

Figure 5: Cluster 1 Map

Cluster 1 represents poverty in the semi-rural metropolitan outskirts. This is the only cluster made up of tracts that were less densely populated than their surrounding metro areas. Not surprisingly then, the housing stock was dominated by owner-occupied, single-family homes. This cluster also had highest percentage of white residents, and was the least distressed of all the clusters in 2000, in terms of both poverty rate and MFI ratio.

Socioeconomic outcomes in Cluster 1 were mixed. Cluster 1 experienced weak housing appreciation and above average increases in poverty, relative to poor census tracts overall. Though all but one of the neighborhood types saw inflation-adjusted income decrease over the course of the 2000s, the $2,390 drop in MFI for Cluster 1 was slightly worse than the average for all neighborhood types. On the other hand, the positive value on mfi.ratio.ch indicates that the within-metro rank of Cluster 1 tracts actually improved over the same period. A likely explanation for the contrast of worse-than-average absolute income change but better-than-average relative income change is that Cluster 1 is populated by tracts located in metro areas that were especially hard-hit by the economic recession of the late-2000s.

The relatively low levels of socioeconomic distress in 2000 might lead one to suspect that this neighborhood type would have been attractive to risk-averse developers. Instead, it saw the lowest levels of both NMTC and LIHTC investment from 2001-2007. Furthermore, this is only neighborhood type in which not a single census tract was targeted by both programs.

Table 5: Top 10 Metro Areas by Percent in Cluster 1

Metropolitan Area	Pct. of Poor Census Tracts in MSA
Tulsa, OK	43.53
Birmingham-Hoover, AL	34.04
Tampa-St. Petersburg-Clearwater, FL	30.94
Pittsburgh, PA	22.78
Nashville-Davidson--Murfreesboro--Franklin, TN	21.35
Austin-Round Rock, TX	17.24
Tucson, AZ	16.46

Oklahoma City, OK	15.00
Houston-The Woodlands-Sugar Land, TX	13.07
Orlando-Kissimmee-Sanford, FL	12.63

3.6.3.2 Cluster 2: Hispanic immigrant gateways

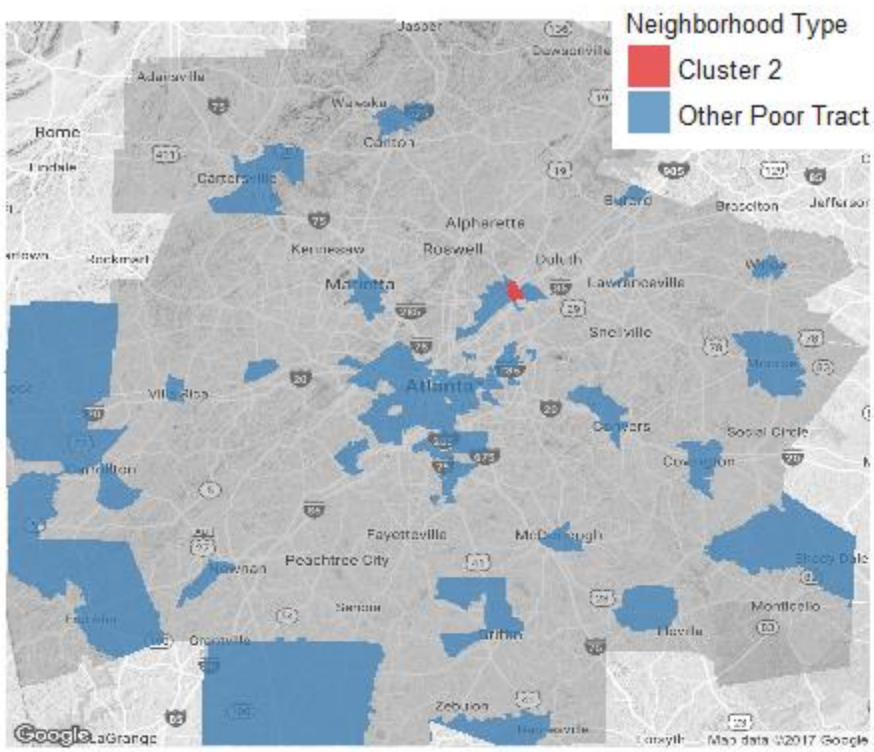

Figure 6: Cluster 2 Map

Cluster 2 census tracts are heavily concentrated in metropolitan areas adjacent to the Mexican border in California and Texas, and in California’s agricultural heartland. This cluster is notable for the overall absence of both white and black non-Hispanic residents, and the dominance of Hispanics, recent immigrants, and foreign-born residents. The residents of these neighborhoods have among the lowest levels of educational attainment, workforce participation, and employment in high-status (management) jobs. Thus, the neighborhood dimension describing high levels of economic distress and low levels of human capital is a defining feature of Cluster 2.

Taken together, these attributes suggest the interpretation of this cluster as a distinct type of immigrant neighborhood. Specifically, these places serve as the initial landing points for large numbers of economic migrants arriving to the United States from Mexico and Central America, many of whom may be undocumented (Hill & Johnson, 2011).

From 2000 to 2009-2013, this cluster remained relatively stable. On two of the socioeconomic indicators- poverty change and unemployment change, the tracts in this cluster fared better than average. On the other hand, home value appreciation was somewhat slower, and MFI declined, both in absolute terms and relative to MFI change in their respective metro areas.

While place-based investment was somewhat more frequent in this Cluster 2 than in Cluster 1, the percentage of census tracts receiving investment for both NMTC and LIHTC was well below average.

Table 6: Top 10 Metro Areas by Percent in Cluster 2

Metropolitan Area	Pct. of Poor Census Tracts in MSA
McAllen-Edinburg-Mission, TX	88.00
El Paso, TX	77.01
San Antonio-New Braunfels, TX	49.13
Fresno, CA	34.00
Los Angeles-Long Beach-Anaheim, CA	26.84
Denver-Aurora-Lakewood, CO	22.12
Houston-The Woodlands-Sugar Land, TX	22.11
Phoenix-Mesa-Scottsdale, AZ	20.58
Riverside-San Bernardino-Ontario, CA	16.99
Dallas-Fort Worth-Arlington, TX	16.71

3.6.3.3 Cluster 3: racially heterogeneous neighborhoods

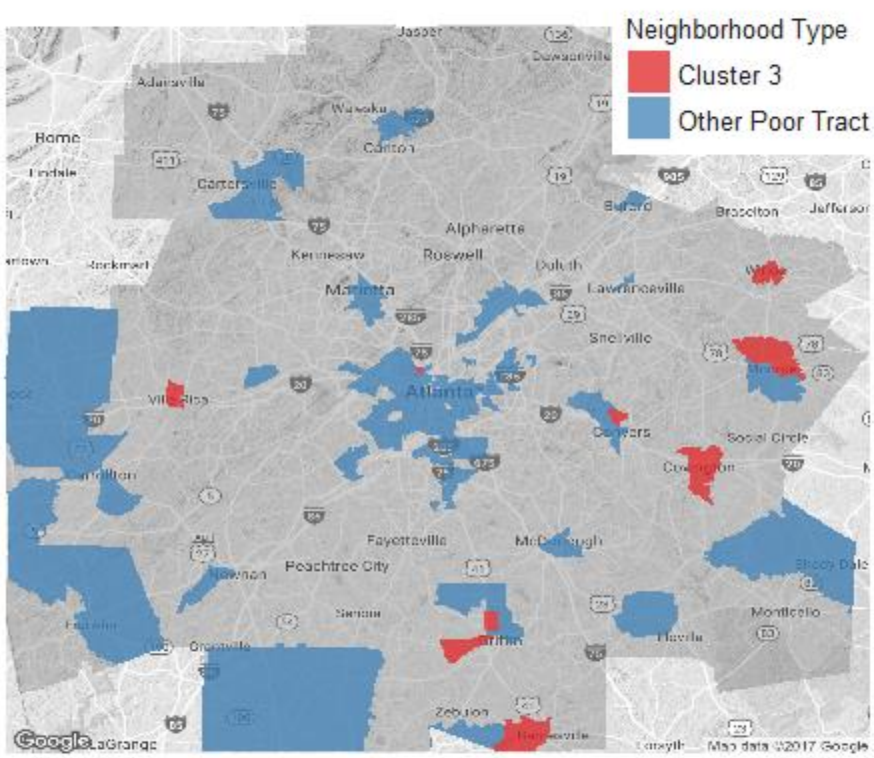

Figure 7: Cluster 3 Map

Cluster 3 was the least common neighborhood type, representing only 3.2 percent of the census tracts included in the study. It is also somewhat difficult to concisely define, as its baseline attributes do not immediately evoke the image of a specific kind of poor place that exists empirically, theoretically, or in the public consciousness. However, the map provides some important context. It shows that only one of the Cluster 3 tracts in metropolitan Atlanta was located within Atlanta city limits. The rest tended to be located in the county seats of the counties making up the periphery of the metro region (e.g. Conyers, Covington, and Griffin, GA). Thus, whereas Cluster 1 represented semi-rural neighborhood poverty, Cluster 3 may represent small-town neighborhood poverty.

Cluster 3 had the second lowest population density; however, these tracts were still somewhat denser than their respective metro areas, which indicates that they tended to be situated in relatively small metro areas that were not highly urbanized. The housing markets in these places were quite weak in 2000, with home values barely half the metro averages and above average vacancy rates.

The demographic profile of this cluster finds that these neighborhoods were home to a relatively even mix of black and white residents who were born in the United States. This is only one of three clusters that was not majority black, white, or Hispanic. Very few of the residents are Hispanic, Asian, or foreign born. Moreover, the population is poorly educated, with an above-average percentage of adults with a high school degree or less, and very few residents with at least a bachelor's degree.

The most notable facet of Cluster 3 is that it suffered significant socioeconomic decline over the course of the 2000s. Cluster 3 was either the worst or second worst performer on all five indicators of socioeconomic change. Place-based investment played little part in mitigating the economic freefall Cluster 3 experienced, as the intensity of investment was below average for both NMTC and LIHTC.

Table 7: Top 10 Metro Areas by Percent in Cluster 3

Metropolitan Area	Pct. of Poor Census Tracts in MSA
Charlotte-Concord-Gastonia, NC-SC	17.07
Indianapolis-Carmel-Anderson, IN	10.31
Louisville/Jefferson County, KY-IN	9.09
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	9.01
Tampa-St. Petersburg-Clearwater, FL	8.84
Pittsburgh, PA	7.22
Miami-Fort Lauderdale-West Palm Beach, FL	6.78
Orlando-Kissimmee-Sanford, FL	6.32
Atlanta-Sandy Springs-Roswell, GA	6.25
Oklahoma City, OK	5.83

3.6.3.4 Cluster 4: moderate-poverty and medium-density

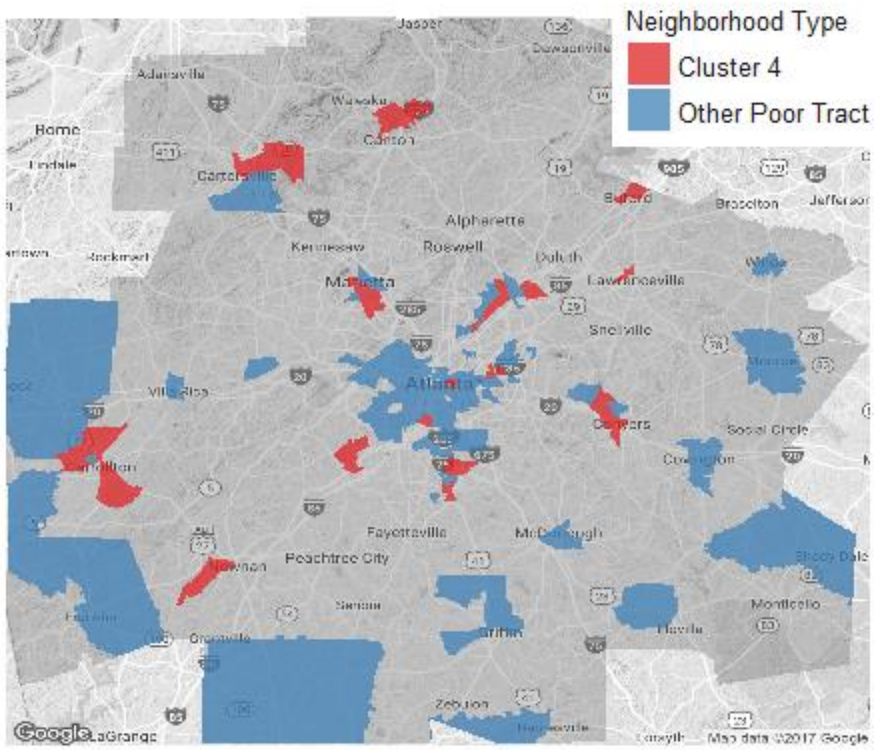

Figure 8: Cluster 4 Map

Cluster 4 was the most common type of poor neighborhood, capturing almost one in five census tracts. Cluster 4 was in a virtual tie with Cluster 1 as having the lowest initial levels of socioeconomic distress in terms of both poverty rate and MFI ratio. While both clusters were majority-white, there was more racial diversity to be found in Cluster 4. The population of Cluster 4 was relatively well-educated and was also more actively engaged with the surrounding labor market than in most other neighborhood types, as indicated by high rates of female labor force participation and employment in management positions.

In contrast to its initial stability, the socioeconomic trajectory of Cluster 4 during the 2000s was worse than the overall average on all five indicators. Similarly, the percentages of census tracts in Cluster 4 that received either NMTC or LIHTC investment was somewhat lower than in other neighborhood types.

Table 8: Top 10 Metro Areas by Percent in Cluster 4

Metropolitan Area	Pct. of Poor Census Tracts in MSA
Portland-Vancouver-Hillsboro, OR-WA	62.96
Seattle-Tacoma-Bellevue, WA	51.75
Las Vegas-Henderson-Paradise, NV	42.57
Sacramento--Roseville--Arden-Arcade, CA	38.21
Denver-Aurora-Lakewood, CO	32.69
Orlando-Kissimmee-Sanford, FL	31.58
Phoenix-Mesa-Scottsdale, AZ	31.05
Minneapolis-St. Paul-Bloomington, MN-WI	30.70
Fresno, CA	30.00
San Diego-Carlsbad, CA	29.05

3.6.4.5 Cluster 5: lower-density segregated black neighborhoods

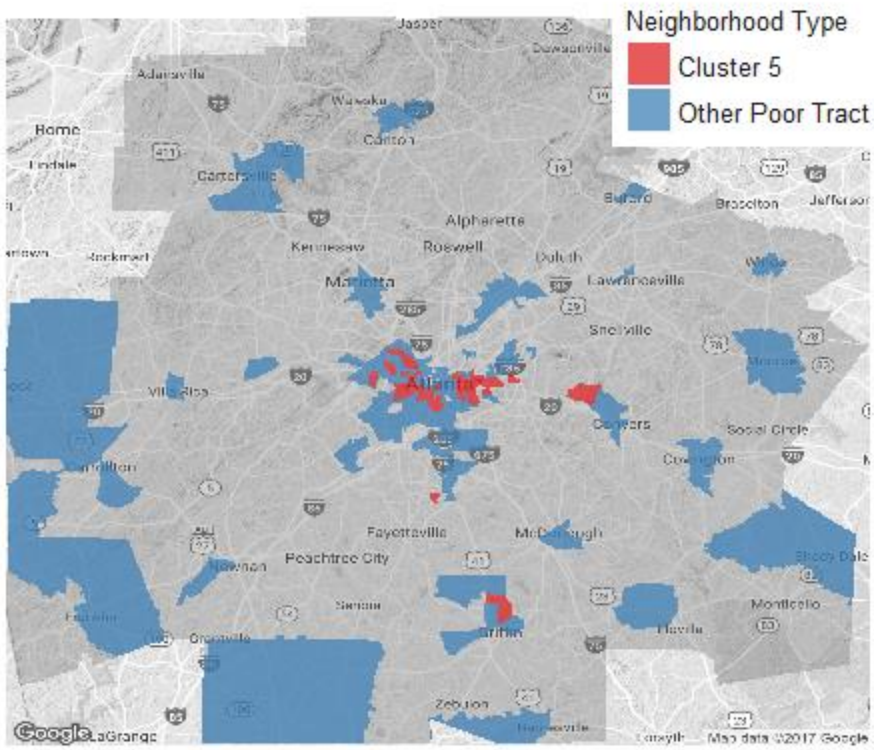

Figure 9: Cluster 5 Map

Even in comparison to other poor places, Cluster 5 is notable for its high poverty rates, as well as income levels that were barely half of the metro averages. The extreme poverty conditions of Cluster 5 disproportionately affected the African American community, as over 86 percent of residents in 2000 were black. This was the most extreme concentration of any racial or ethnic group among the ten neighborhood types. The social and economic isolation of the black population is perhaps the most well-known and well-documented aspect of poverty in the US. The persistent dislocation of the African American community from local labor markets is one of the major themes to have emerged in the literature on concentrated poverty in the last three decades (Massey, 1993; Wilson, 2012). Thus, it is not surprising to see Cluster 5 typified by year 2000 attributes that suggest a lack of economic opportunity, such as low levels of education and female labor force participation, very few residents employed in high-status jobs, and high rates of female-headed households.

Though the poverty and racial isolation just described may evoke stereotyped images of inner-city ghettos, these tracts were among the least densely populated. Looking at the metro areas where Cluster 5 was most common in 2000, two distinct contexts emerge. The first places Cluster 5 into smaller metro areas in the Mississippi River Delta, and the Deep South more generally. The second context places Cluster 5 tracts into some of the primary destinations for the waves of rural southern blacks during the Great Migration (McHugh, 1987). Furthermore, some of the larger metro areas where this neighborhood type is common, such as Detroit, St. Louis, and Baltimore, are commonly associated with racial segregation, as well as difficult and sometimes traumatic race relations, both by research and in the public consciousness. With above average vacancy rates and median home prices less than half the metro averages, the neighborhoods in this cluster would likely show some of the telltale physical signs of concentrated poverty, including a housing stock that could be described as run down, or potentially even dilapidated.

Cluster 5 recorded the worst 2000 to 2009-2013 outcomes of all the neighborhood types on the MFI, unemployment, and median home values indicators, and were second worst in MFI ratio and poverty rate changes. Unfortunately, there was relatively little place-based investment in Cluster 5 tracts to help mitigate the wholesale socioeconomic decline, as NMTC investment in Cluster 5 was well below average, while LIHTC investment was right at the group mean.

Table 9: Top 10 Metro Areas by Percent in Cluster 5

Metropolitan Area	Pct. of Poor Census Tracts in MSA
Detroit-Warren-Dearborn, MI	58.68
Memphis, TN-MS-AR	51.40
St. Louis, MO-IL	49.33
Baltimore-Columbia-Towson, MD	48.19
Birmingham-Hoover, AL	39.36
Kansas City, MO-KS	35.83
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	34.53
New Orleans-Metairie, LA	34.42
Cleveland-Elyria, OH	29.78
Virginia Beach-Norfolk-Newport News, VA-NC	26.73

3.6.3.6 Cluster 6: the "average" poor neighborhood

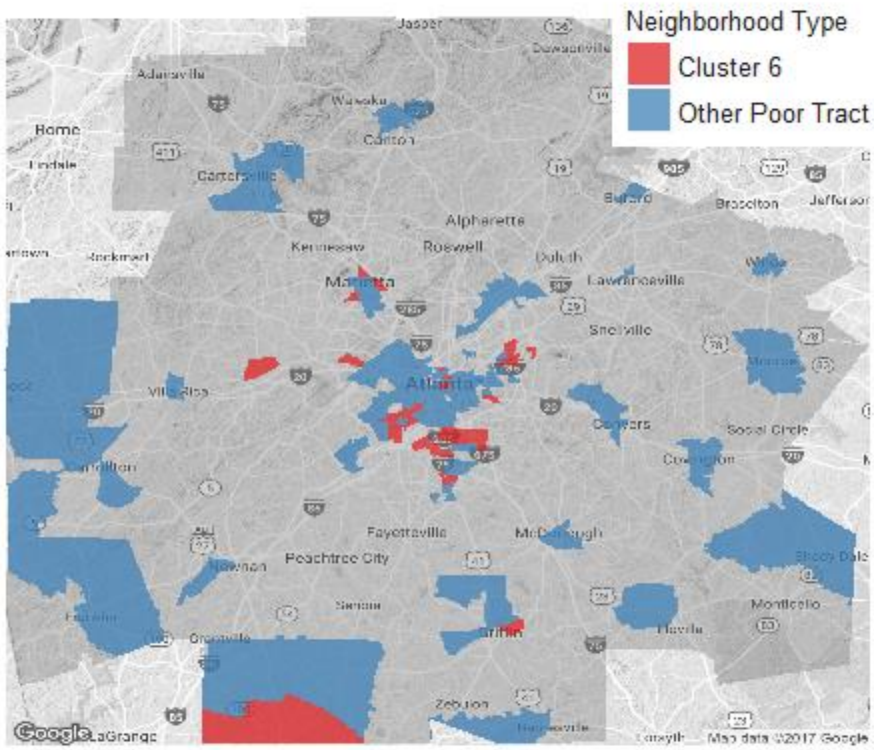

Figure 10: Cluster 6 Map

Cluster 6 was perhaps the most difficult of all neighborhood types to describe, as it did not stand out compared to poor census tracts overall on any year 2000 neighborhood attribute. On the other hand, the socioeconomic trajectory of Cluster 6 was at least one standard deviation worse than the metro average on all five change indicators. For NMTC and LIHTC investment intensity, the same "average" pattern reemerged.

Table 10: Top 10 Metro Areas by Percent in Cluster 6

Metropolitan Area	Pct. of Poor Census Tracts in MSA
Washington-Arlington-Alexandria, DC-VA-MD-WV	31.71
Providence-Warwick, RI-MA	31.37
Orlando-Kissimmee-Sanford, FL	28.42
Boston-Cambridge-Newton, MA-NH	28.04
Sacramento--Roseville--Arden-Arcade, CA	27.64
Minneapolis-St. Paul-Bloomington, MN-WI	26.32
Virginia Beach-Norfolk-Newport News, VA-NC	25.74
Cincinnati, OH-KY-IN	25.41
Oklahoma City, OK	24.17
Buffalo-Cheektowaga-Niagara Falls, NY	23.46

3.6.3.7 Cluster 7: black distressed urban neighborhoods

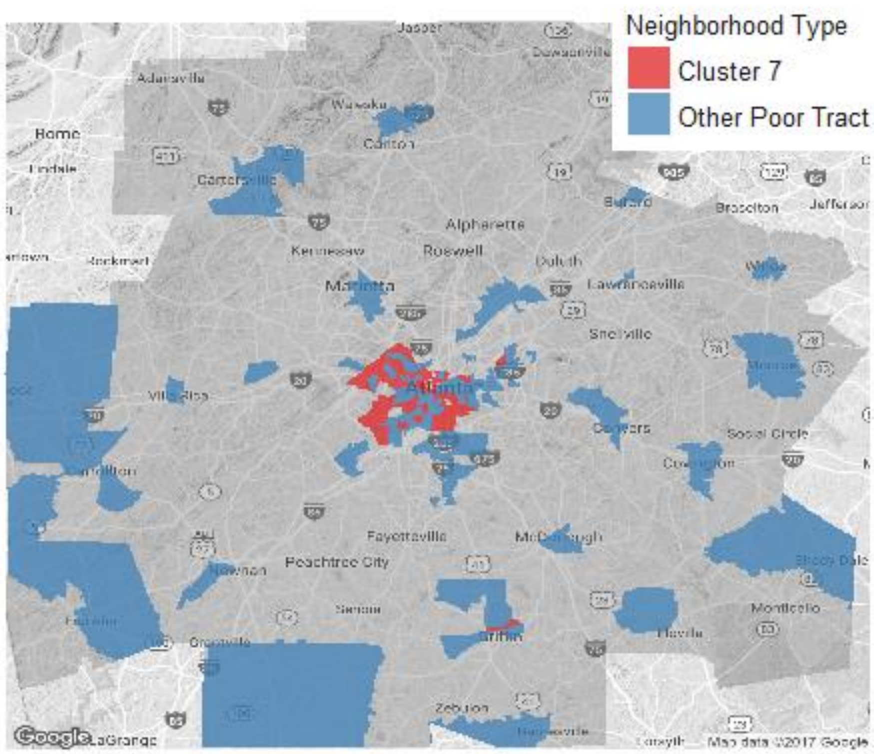

Figure 11: Cluster 7 Map

Cluster 7 was the most severely distressed type of poor neighborhood in 2000, as it had the lowest average MFI ratio and highest poverty rate. Three quarters of Cluster 7 residents were black, reinforcing the persistent link between race and concentrated poverty. Other indicators of population and neighborhood distress were also present, as these tracts had the highest unemployment rates and highest vacancy rates.

In these important respects, Cluster 7 and Cluster 5 appear to subtle variations of the same basic kind of poor and racially isolated neighborhood. However, there are some notable differences. For one, Cluster 7 tracts were much more densely populated- they had twice the average population density as Cluster 5 tracts, and were also twice as dense as their metro averages. In terms of 2000 to 2009-2013 change, Cluster 7 fared much better than Cluster 5, and better than poor census tracts overall on all five indicators. In particular, MFI ratio change was positive in Cluster 7 tracts, indicating that these tracts improved their status within their respective metropolitan areas during the 2000s.

Furthermore, whereas Cluster 5 tracts had below average levels of place-based investment, Cluster 7 had the highest percentage of tracts with LIHTC activity and the second highest percentage of tracts with NMTC activity.

Table 11: Top 10 Metro Areas by Percent in Cluster 7

Metropolitan Area	Pct. of Poor Census Tracts in MSA
Rochester, NY	44.29
Milwaukee-Waukesha-West Allis, WI	34.45

Virginia Beach-Norfolk-Newport News, VA-NC	27.72
Chicago-Naperville-Elgin, IL-IN-WI	26.97
Atlanta-Sandy Springs-Roswell, GA	25.00
Cincinnati, OH-KY-IN	24.59
New Orleans-Metairie, LA	22.73
Buffalo-Cheektowaga-Niagara Falls, NY	20.99
Memphis, TN-MS-AR	19.63
Cleveland-Elyria, OH	19.10

3.6.3.8 Cluster 8: diverse distressed urban neighborhoods

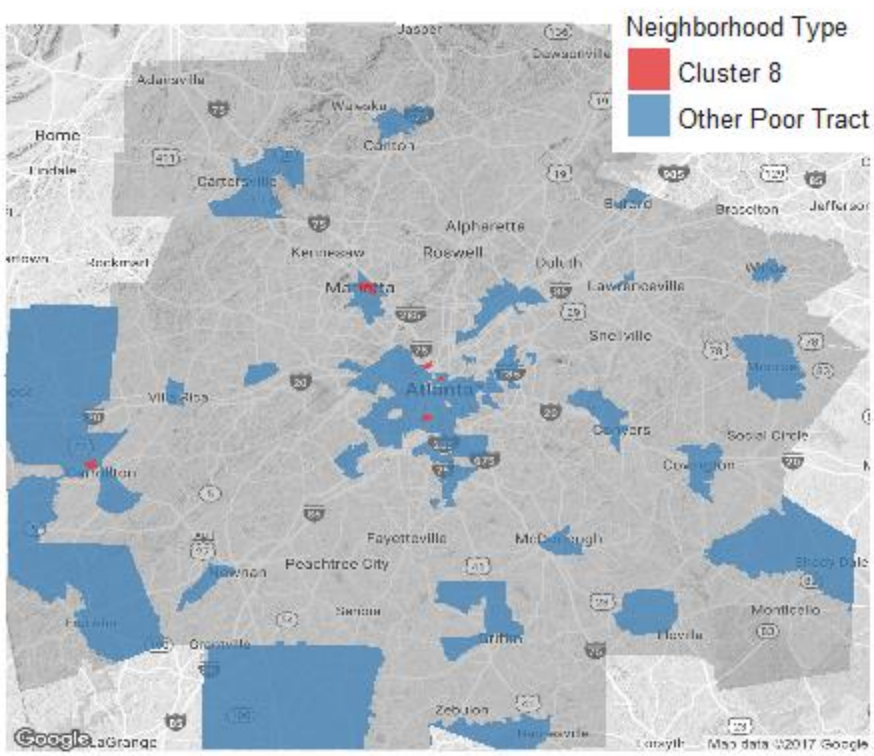

Figure 12: Cluster 8 Map

Cluster 8 was in a virtual tie with Cluster 7 as the most economically distressed neighborhood type in 2000. While Cluster 7 poverty was associated with the racial and economic segregation of blacks, Cluster 8 was much more diverse, with a large Hispanic population and high percentage of foreign-born residents.

With a poorly educated adult population, low levels of workforce participation, and few people working in high-status management positions, Cluster 8 appears to most heavily reflect the role of human capital in the formation and persistence of concentrated poverty.

Despite its weak starting point, Cluster 8 remained quite stable from 2000 to 2009-2013 in terms of poverty, unemployment, and income levels. Home value growth in Cluster 8 was greater than in other neighborhood types during the 2000s as well.

Cluster 8 attracted a significant amount of place-based investment during the 2000s, as NMTC investment was highest in this cluster, and was in a virtual tie for the highest levels of LIHTC investment with Cluster 7 tracts.

Table 12: Top 10 Metro Areas by Percent in Cluster 8

Metropolitan Area	Pct. of Poor Census Tracts in MSA
Providence-Warwick, RI-MA	40.20
Fresno, CA	27.00
New York-Newark-Jersey City, NY-NJ-PA	21.86
Boston-Cambridge-Newton, MA-NH	18.69
Las Vegas-Henderson-Paradise, NV	17.82
Los Angeles-Long Beach-Anaheim, CA	17.78
Riverside-San Bernardino-Ontario, CA	16.99
San Diego-Carlsbad, CA	16.76
San Francisco-Oakland-Hayward, CA	15.90
Minneapolis-St. Paul-Bloomington, MN-WI	15.79

3.6.3.9 Cluster 9: high-density immigrant gateways in big metropolitan areas

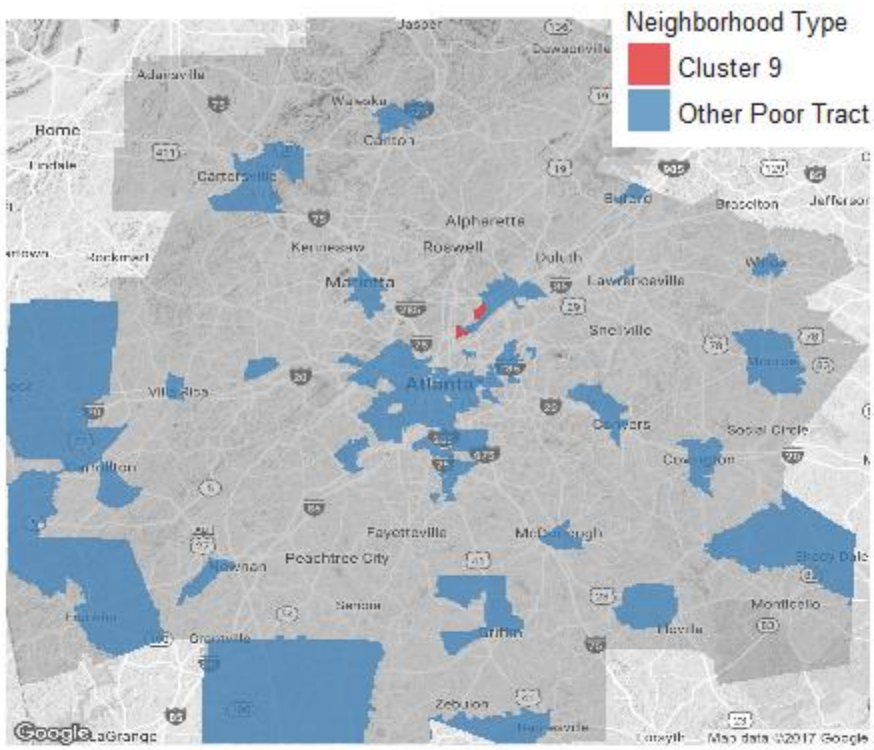

Figure 13: Cluster 9 Map

By a wide margin, Cluster 9 was the most densely populated neighborhood type. With 32,941 people per square mile, the average census tract in Cluster 9 had a higher population density than New York City. Despite having the highest levels of overall density, these tracts are ranked second in terms of density relative to density in the surrounding metro. This discrepancy suggests that this neighborhood type is a feature of large urban centers. Thus, it is little surprise that this was the most common type of neighborhood in the nation's two largest urban agglomerations, New York City and Los Angeles, and the second most common poor neighborhood type in Chicago and San Francisco. Cluster 9 tracts were prominent in many other metro areas with large immigrant populations.

Multi-family rental housing was especially common in Cluster 9. With large populations came significant housing demand as well, as the percentage of housing units that were vacant in 2000 was lower in Cluster 9 than in any other type of poor neighborhood.

Whereas some of the other immigrant clusters were specifically tied to immigration from Latin America, Cluster 9 tracts had the highest concentration of Asian residents in 2000, suggesting that proximity to the Mexican border is not the primary explanation for the large numbers of foreign-born residents.

Cluster 9 was on a path of strong socioeconomic ascent from 2000 to 2009-2013. While poverty increased in all ten neighborhood types over the course of the 2000s, it increased the least in Cluster 9. The most notable aspect of ascent may be the explosion in housing prices. The median home in Cluster 9 increased in value by nearly $132,000 during the 2000s, more than three times the average for poor census tracts overall.

Despite the clear upward socioeconomic trajectory, place-based investment in Cluster 9 was average. The percentage of Cluster 9 tracts with NMTC activity was slightly above average, while LIHTC activity was slightly below.

Table 13: Top 10 Metro Areas by Percent in Cluster 9

Metropolitan Area	Pct. of Poor Census Tracts in MSA
New York-Newark-Jersey City, NY-NJ-PA	35.23
Los Angeles-Long Beach-Anaheim, CA	30.31
San Diego-Carlsbad, CA	20.67
Chicago-Naperville-Elgin, IL-IN-WI	19.10
San Francisco-Oakland-Hayward, CA	17.44
Miami-Fort Lauderdale-West Palm Beach, FL	16.71
Washington-Arlington-Alexandria, DC-VA-MD-WV	13.41
Boston-Cambridge-Newton, MA-NH	11.68
Las Vegas-Henderson-Paradise, NV	8.91
Riverside-San Bernardino-Ontario, CA	8.11

3.6.3.10 Cluster 10: college town neighborhoods

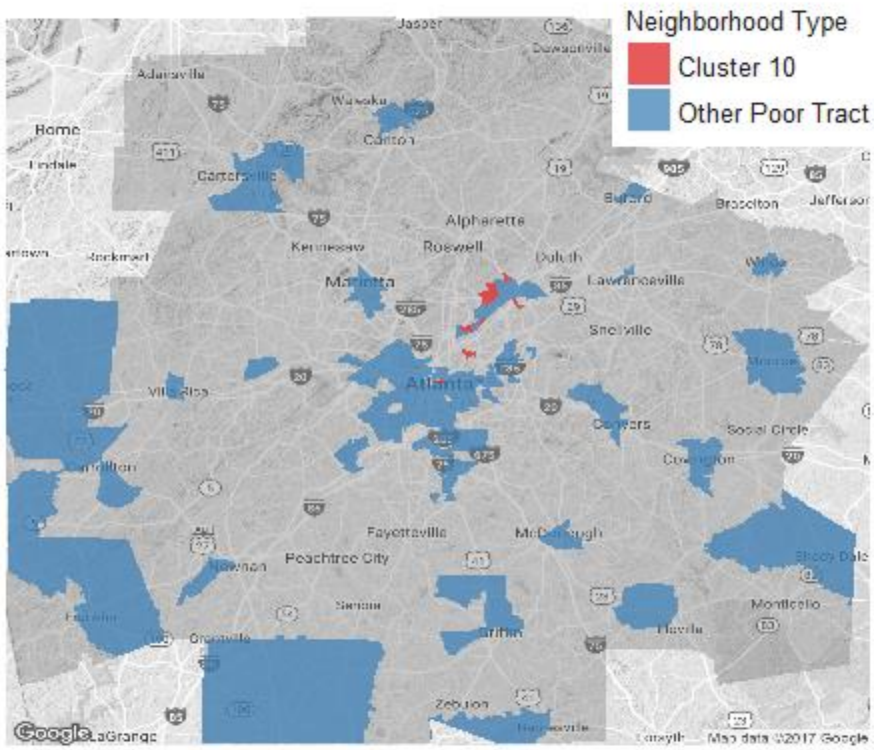

Figure 14: Cluster 10 Map

As discussed in the methods section, I excluded from the analysis a small subset of "high poverty-high income" census tracts that were found to be poor primarily due to their proximity to large university campuses. However, even after taking this step, the cluster analysis still identified a group of highly educated, moderately distressed census tracts as a distinct neighborhood type. Cluster 10 was the most common neighborhood type in many smaller metro areas in which the local economy is defined by a large research university, such as Iowa City, IA, Ithaca, NY, and Lawrence, KS.

Cluster 10 arguably improved more than any other neighborhood type during the 2000s. For one, it was the only cluster in which inflation-adjusted median income increased. It was also the only cluster in which, by 2009-2013, the average MFI ratio had increased to above 80 percent threshold that serves as one of the primary NMTC eligibility criteria. Thus, many of the census tracts in Cluster 10 that were eligible for NMTC in 2000 based on the MFI ratio requirement were likely no longer eligible by the end of the decade.

The only indicator in which Cluster 10 was not among the top one or two performers was poverty. The contrast of steady poverty against a backdrop of significant improvement on the other four socioeconomic indicators lends support for the idea that the cause of poverty in Cluster 10 is a function of student housing, which is annually replenished with a new cohort of temporarily poor freshmen.

The biggest contrast between NMTC and LIHTC investment levels occurred in Cluster 10, where NMTC investment was 1.2 percentage points above the overall average while LIHTC investment was 2.08 percentage points below average.

Table 14: Top 10 Metro Areas by Percent in Cluster 10

Metropolitan Area	Pct. of Poor Census Tracts in MSA
Austin-Round Rock, TX	17.24
Minneapolis-St. Paul-Bloomington, MN-WI	15.79
San Francisco-Oakland-Hayward, CA	14.36
Nashville-Davidson--Murfreesboro--Franklin, TN	13.48
Seattle-Tacoma-Bellevue, WA	13.16
Boston-Cambridge-Newton, MA-NH	11.68
Denver-Aurora-Lakewood, CO	11.54

Portland-Vancouver-Hillsboro, OR-WA	11.11
Columbus, OH	10.78
Washington-Arlington-Alexandria, DC-VA-MD-WV	9.76

3.6.4 SES Change and Investment Patterns

3.6.4.1 SES change

Figure 15 plots the 2000 to 2009-2013 changes in MFI, MFI ratio, poverty, unemployment, and home values for each neighborhood type. All values were standardized as z-scores, and poverty and unemployment were recoded to give a uniform interpretation for positive and negative values on all change indicators.

Overall, the direction of socioeconomic change for each neighborhood type was consistent across all measures. One exception is Cluster 2, Hispanic Immigrant Gateway neighborhoods, which saw less income and home value growth than other poor neighborhood types, yet fared better in terms of poverty and unemployment change. The relative stability in Cluster 2 on the latter two indicators may reflect one of the few positive externalities recognized in the literature as arising out of certain contexts of concentrated poverty. Because many gateway neighborhoods are populated by residents hailing from the same city, or even the same neighborhood in their country of origin (Massey, Goldring, & Durand, 1994), those preexisting social ties and institutions may facilitate the assimilation of new arrivals by providing enhanced access to social services and employment opportunities (P. A. Jargowsky, 2009).

The other notable exception is Cluster 10, College Town Neighborhoods. The contrast of slightly above average growth in the poverty rate against strong performance on the other four measures seen is most likely a function of the annual churn of graduating seniors being replaced with new cohorts of temporarily poor freshmen, which naturally makes poverty an enduring feature in these neighborhoods, regardless of other socioeconomic trends.

As mentioned earlier, I organized the neighborhood clusters in order from least to most densely populated, relative to the population density of the surrounding metro area. Thus, Figure 15 shows a clear association between higher initial relative population density and better subsequent socioeconomic outcomes. Socioeconomic ascent was almost entirely concentrated in the four clusters with the highest relative population densities. Clusters 1 and 2, which had the lowest relative densities, experienced below-average outcomes on multiple indicators, while Clusters 3 through 6 experienced worse outcomes than the average poor census tract on all five indicators of socioeconomic change.

Lending further support for the notion that population density was one of the primary drivers of socioeconomic ascent for poor neighborhoods during the 2000s, neither the neighborhood distress index nor the black isolation index was significantly related to any of the socioeconomic change indicators. On the other hand, the neighborhood dimension represented by the urbanization index was significantly correlated with 2000 to 2009-2013 income growth, $r = .69$, $p < .05$, home value growth, $r = .65$, $p < .05$ and falling unemployment $r = .75$, $p < .05$.

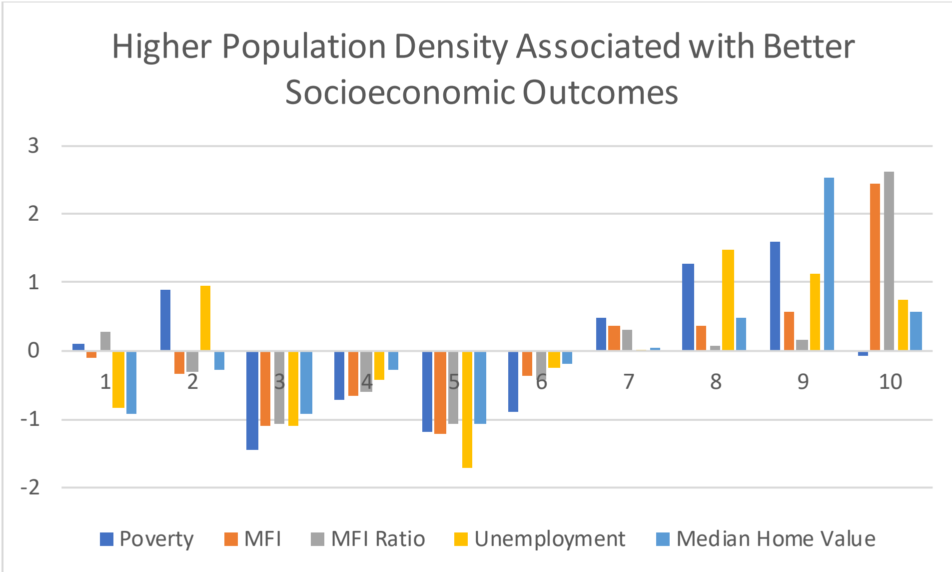

Figure 15: 2000 to 2009-2013 Socioeconomic Changes by Cluster

3.6.4.2 NMTC and LIHTC investment

There was a significant relationship between the percent of census tracts in a neighborhood cluster that received NMTC investment and the percent that received LIHTC investment, $r = .83$, $p < .01$. The percent of census tracts that received both NMTC and LIHTC investment was also significantly correlated with NMTC investment, $r = .97$, $p < .0001$, and LIHTC investment, $r = .78$, $p < .01$.

The consistent parallels in NMTC investment and LIHTC investment within and across neighborhood types suggests at least two things. First, it lends support for the idea that, because NMTC and LIHTC employ similar market-driven mechanisms to deliver resources into distressed areas, they are drawn towards the same types of poor places. Second, it shows that the neighborhood dimensions uncovered by the PCA, which provided the basis for classifying distinct types of poor neighborhoods, do bear some meaningful resemblance to the unobserved neighborhood characteristics that NMTC and LIHTC developers pay attention to and care about when making location decisions. To the degree that these assertions are accurate, using this typology to further investigate NMTC and LIHTC investment may yield important new insights about the unobserved neighborhood-level drivers of treatment selection in these kinds of market-driven programs.

Visualizing NMTC and LIHTC investment patterns across the neighborhood types provides an immediate clue about at least one important factor. Figure 16 shows a clear trend towards increasing levels of NMTC and LIHTC investment in more densely populated clusters. Thus, it is not surprising that the urbanization index was significantly correlated with the percent of census tracts that received both NMTC and LIHTC investment, $r = .78$, $p < .01$, the percent that received NMTC, $r = .83$, $p < .01$, and was significant at the ten percent level for LIHTC investment. There was no significant association between NMTC or LIHTC investment and either of the two other neighborhood dimensions.

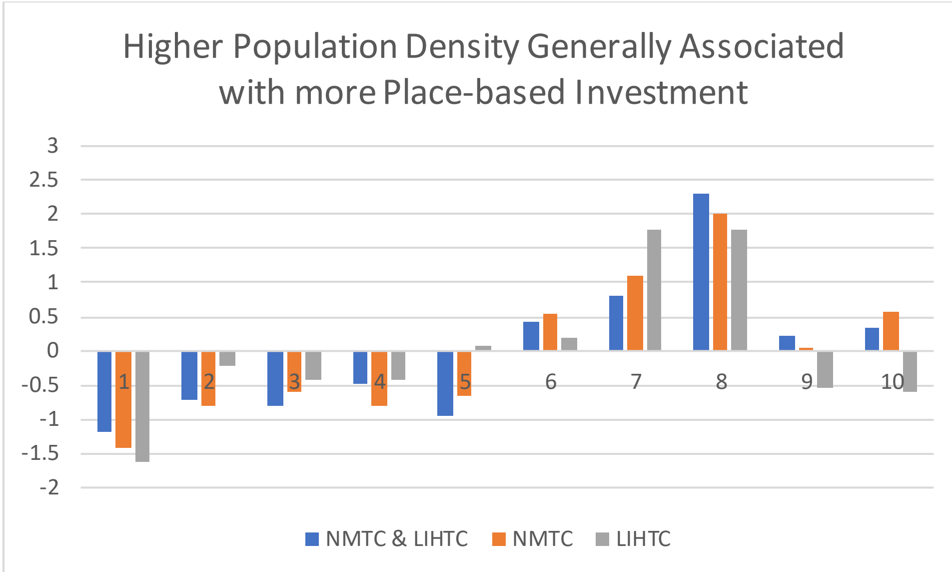

Figure 16: NMTC and LIHTC Investment Intensity by Cluster

However, the sharp drop in the percentage of census tracts receiving investment in clusters 9 and 10 suggests that NMTC and LIHTC locational patterns during the 2000s were not only a function of urbanization. Further analysis revealed that the initial level of socioeconomic distress in a census tract was the other major factor driving NMTC and LIHTC locational patterns. Figure 17 highlights the marked difference in the initial poverty rates and MFI ratios of high-density clusters with high levels of NMTC and LIHTC investment (clusters 7 and 8) and those with relatively little investment (clusters 9 and 10). On both measures, Cluster 7 and Cluster 8 were the two most socioeconomically distressed neighborhood types in 2000. In contrast, Cluster 9 was average among neighborhood types on both measures, while Cluster 10 was somewhat better off than the average for all neighborhood types in 2000.

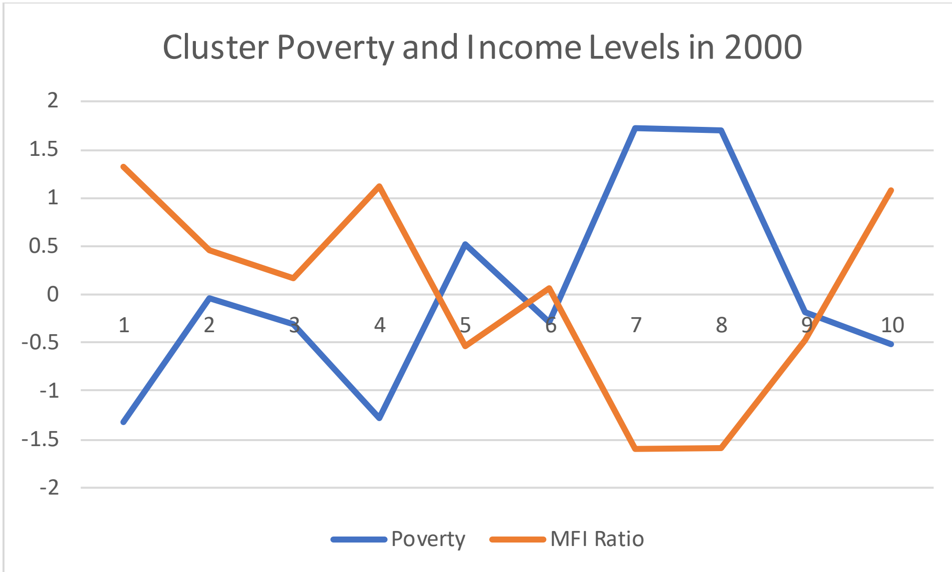

Figure 17: Standardized Poverty Rate and MFI Ratio by Cluster in 2000

The link between initial levels of socioeconomic distress and subsequent NMTC and LIHTC investment may also explain why there was no significant association between a neighborhood type's 2000 to 2009-2013 socioeconomic change and the frequency of place-based investment. As discussed in Chapter 2 and at the beginning of this chapter, both NMTC and LIHTC include provisions intended to influence the behavior of the actors involved in their administration and use by providing various additional incentives for locating projects into areas with higher levels of socioeconomic distress than basic program requirements dictate. Thus, the apparent attraction of NMTC and LIHTC investment to highly distressed neighborhoods over places with similar levels of population density that were only moderately distressed, may be a function of these provisions, rather than a reflection of the true preferences of market actors.

This finding indicates that these provisions are effective tools for distributing place-based investment dollars to a wider and more diverse array of distressed places than might otherwise be observed, without being so restrictive as to eliminate program demand. However, the uneven application of these provisions across all eligible places is consequential in the context of this study. Given the relatively loose criteria I established for identifying a study population of low-income, high-poverty census tracts, the study area is effectively divided into two key subgroups in which different combinations of NMTC and LIHTC provisions apply. The first subgroup includes the moderately distressed census tracts that met the basic NMTC requirements, but did not meet the stricter poverty/income/unemployment requirements to be defined as "high distress" under NMTC, and similarly did not meet the poverty/income requirements for additional LIHTC tax credits. The second consists of census tracts that met the additional poverty and income requirements to receive full consideration and favor of both NMTC and LIHTC.

The inclusion of census tracts governed by two different sets of incentives complicates one of the main goals of this study, which is to use the observed locational patterns of NMTC and LIHTC investment across neighborhood types to discover the latent drivers of treatment selection related to the preferences of developers. Because program provisions effectively steer development towards the neighborhood types primarily populated by high distress census tracts, the true preferences of developers are obscured.

3.6.5 Analysis of Severely distressed Subset

To eliminate, or at least reduce, the influence of the various NMTC and LIHTC program provisions on developers' decision-making processes, I ran the same analysis just discussed on a subset of severely distressed census tracts. As mentioned in the Methods section, this severely distressed subset consists of 5,161 census tracts that in 2000 had both (a) greater than 25 percent poverty and (b) MFI ratio less than 60 percent. Descriptive statistics are provided in Table 15, and main results and analysis are presented below.

Table 15. Descriptive Statistics of Severely distressed Clusters

Cluster	1	2	3	4	5	6	7	8
n	517	546	956	481	603	958	796	304
Year 2000 Attributes (% unless noted)								
Poverty	29.42	31.88	34.56	49.39	34.38	34.06	36.7	45.23
MFI Ratio (tract/metro)	53.24	51.52	46.85	31.41	45.78	45.75	43.43	32.64
Unemployment	10.81	12.07	16.17	23.27	14.64	12.87	14.17	18.93
Black	32.86	4.68	88.30	85.59	72.58	12.92	37.00	20.77
Hispanic	22.02	79.71	2.60	5.28	7.16	54.53	23.58	56.99
Asian	3.17	4.24	0.53	0.96	1.55	8.91	4.33	5.49
Recent immigrant	7.45	19.31	0.96	2.02	3.75	19.89	9.85	15.26
Foreign-born	14.11	43.22	2.01	3.95	7.11	40.12	18.67	31.81
High school or less	68.18	81.22	70.40	75.70	65.60	72.28	60.79	76.18
Bachelors or more	9.30	4.93	6.87	5.91	10.64	9.92	16.81	7.69
Females in labor force	52.18	43.10	50.62	45.65	54.54	46.00	52.45	39.67
Work in management	17.69	11.90	17.11	16.11	20.47	17.03	23.84	17.45
Vacancy rate	11.04	5.80	15.45	16.44	14.60	7.46	10.71	7.68
Housing owner-occupied	48.16	42.49	50.84	25.70	32.21	25.48	21.38	10.27
Pop density (mi^2)	6215	11725	6959	9025	10681	23528	17997	43186
Pop. density ratio (tract/metro)	152.24	162.71	173.38	185.26	195.42	212.99	223.78	261.59
Housing in multi-unit structure	34.38	35.29	27.71	58.66	58.77	65.33	73.46	88.46
Home value ratio (tract/metro)	0.53	0.58	0.42	0.47	0.59	0.67	0.70	0.73
Neighborhood Dimension z-scores								
Class Status	-0.26	-1.55	0.92	1.34	0.80	-0.98	0.08	-0.52
Urbanization	-0.82	-0.75	-0.90	0.44	0.14	0.35	0.82	1.37
Black Socioeconomic Isolation	-0.82	0.17	-0.19	1.40	-0.48	0.03	-0.39	1.35
2000 to 2009-2013 SES Change								

Table 15 (continued)

Poverty	5.31	1.94	5.72	0.00	4.60	1.07	2.73	-3.54
MFI	-2913	-2321	-4454	1081	-1381	-768	2641	3232
MFI Ratio	-0.88	-0.76	-2.46	3.88	1.07	0.39	4.54	4.22
Unemployment	6.57	2.19	8.05	2.95	6.10	2.08	2.00	-2.34
Median home value ($)	22200	40415	6501	32104	39193	90046	73639	115122
2003-2007 NMTC/LIHTC Investment								
NMTC and LIHTC	1.55	0.92	0.63	1.04	1.82	2.09	3.02	3.62
NMTC	5.42	4.76	3.87	7.69	7.46	8.66	9.92	10.53
LIHTC	16.83	14.10	14.33	19.33	19.73	15.76	19.72	31.58

3.6.5.1 Neighborhood dimensions

As before, the first step was to enter the thirteen neighborhood indicators into a PCA. The variables again coalesced around three neighborhood dimensions. The component loadings, shown in Table 16, find that the same underlying dimensions that described the full set of high- and moderate-distress census tracts describe severely distressed census tracts alone, with only minor differences.

Table 16. Component Loadings for Severely distressed Tracts

	TC1	TC2	TC3
black.pct.00	**0.89**	-0.17	0.01
other.race.00	**-0.89**	0.1	0.24
hh_female_kids.pct.00	**0.82**	0.11	0.23
homes_vacant.pct.00	0.61	**-0.2**	0.09
own.pct.00	0.1	**-0.91**	-0.12
homes_multi_unit.pct.00	-0.07	**0.9**	-0.05
mhmval.00.ratio	-0.26	0.61	-0.27
density.00.ratio	-0.02	**0.38**	**-0.09**
hs.pct.00	-0.27	-0.41	**0.71**
female_labor.pct.00	0.36	0.14	**-0.71**
poverty.pct.00	0.27	**0.25**	**0.69**
mfi.ratio.00	-0.29	-0.42	**-0.65**
unemp.pct.00	0.37	0.07	**0.54**

The first neighborhood dimension is an index of black isolation. The second dimension is an urbanization index that, in the severely distressed case, places more emphasis on relative housing prices than relative population density. The third dimension is an index of neighborhood distress that incorporates educational attainment and job status of residents as important definitional components. The main point of departure between this and the earlier model, is that the black isolation index explains a larger proportion of the variance in the data when only severely distressed tracts are considered.

3.6.5.2 Neighborhood Types

The second step was to run a cluster analysis on the neighborhood dimensions. The cluster solution with the highest BIC, and thus the best model fit, came from an algorithm producing eight clusters of varying shape, equal volume, and varying orientation (VEV). Table 17 shows the redistribution of the severely distressed census tracts from the original cluster to which they belonged to their new cluster in the 8-cluster solution. Looking across each row, the original clusters 1, 4, and 10 were almost entirely composed of moderately-distressed census tracts that were excluded from this part of the analysis. For the original neighborhood clusters that contained larger proportions of severely distressed tracts, those tracts were in some cases redistributed almost entirely to a single severely distressed cluster (original clusters 2, 5), while others were divided between two or three severely distressed clusters (original clusters 3, 6, 9), and a couple were spread across several severely distressed clusters (original clusters 7, 8). Looking down each column, the severely distressed clusters were for the most part populated by subgroups of census tracts from between one and three of the original clusters.

3.6.5.3 SES Change and Investment Patterns

Many of the patterns and trends uncovered in the primary analysis reemerged when severely distressed census tracts were examined alone. For example, figure 3.6 visualizes the clear and consistent positive association between relative population density and socioeconomic trajectory. Another similarity that carried over is the parallel patterning of NMTC and LIHTC investment across severely distressed neighborhood clusters. There was a significant relationship between the percent of census tracts in a neighborhood cluster that received NMTC investment, and the percent that received LIHTC investment, $r = .75$, $p < .05$. The percent of census tracts that received both

NMTC and LIHTC investment in a neighborhood cluster was also significantly correlated with NMTC investment, $r = .90$, $p < .01$, and LIHTC investment, $r = .80$, $p < .05$.

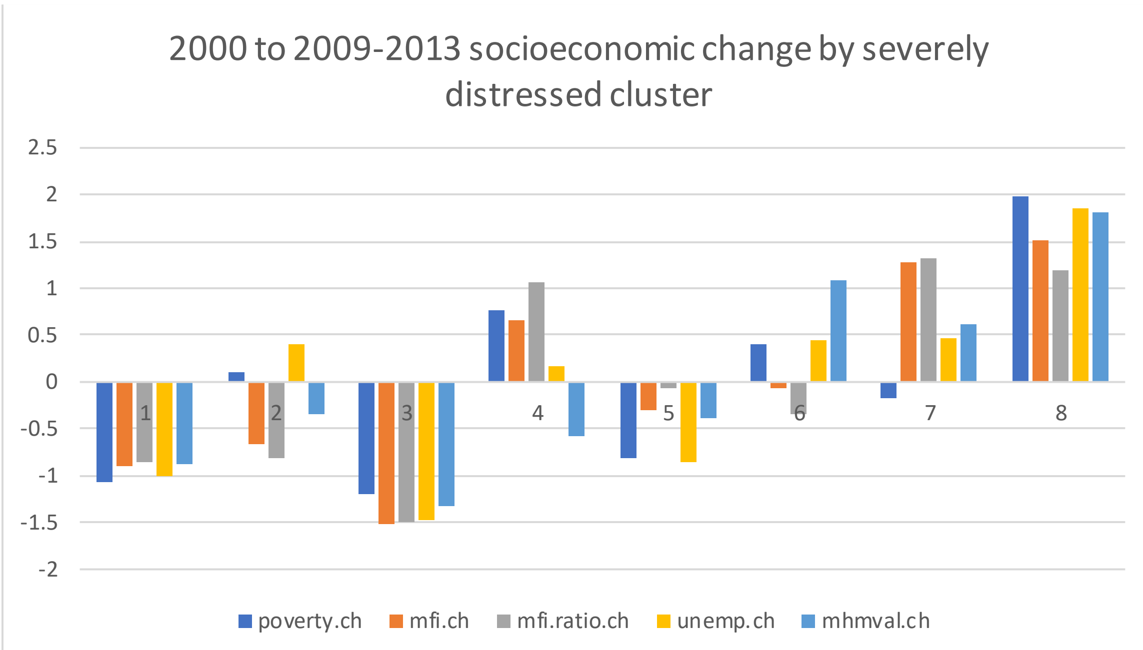

Figure 18. SES Change by Severely distressed Cluster

On the other hand, the analysis of severely distressed tracts alone revealed some points of departure relevant to this study. In the initial analysis, when both moderate- and severely distressed tracts were included, levels of NMTC and LIHTC investment in a neighborhood type were not significantly correlated with any of the socioeconomic change indicators. This was unexpected, as recent studies point out that developers utilizing both NMTC and LIHTC are likely to actively seek out areas that, at least in their minds, are on an upward socioeconomic trajectory.

There are at least three possible explanations for the discrepancy between the literature and my findings. The first is that, as discussed earlier, the study population is effectively divided into two subgroups of distressed places according to the relevance of various determinants of site selection. Another possibility is that developers are motivated to locate projects into socioeconomically ascending areas, but lack either the information or insight to make accurate predictions about a poor neighborhood's future state. Third, it could be the case that developers' location decisions are motivated by factors unrelated to socioeconomic trajectory.

When severely distressed census tracts were examined alone, levels of NMTC and LIHTC investment in a neighborhood type were significantly correlated with multiple aspects of socioeconomic change. Thus, it appears that the first explanation is the most likely. By narrowing the focus to a subset of places where all relevant program provisions have been satisfied, NMTC and LIHTC locational patterns can be investigated in contexts where there are no explicit external factors forcing developers to weigh their natural preferences for neighborhoods bearing certain combinations of attractive attributes against incentives or disincentives unrelated to these attributes.

Having removed the influence of provisions designed to make moderate-distress census tracts less attractive that severely distressed ones, Figure 3.7 shows a positive association between relative population density and frequency of place-based investment that is uninterrupted.

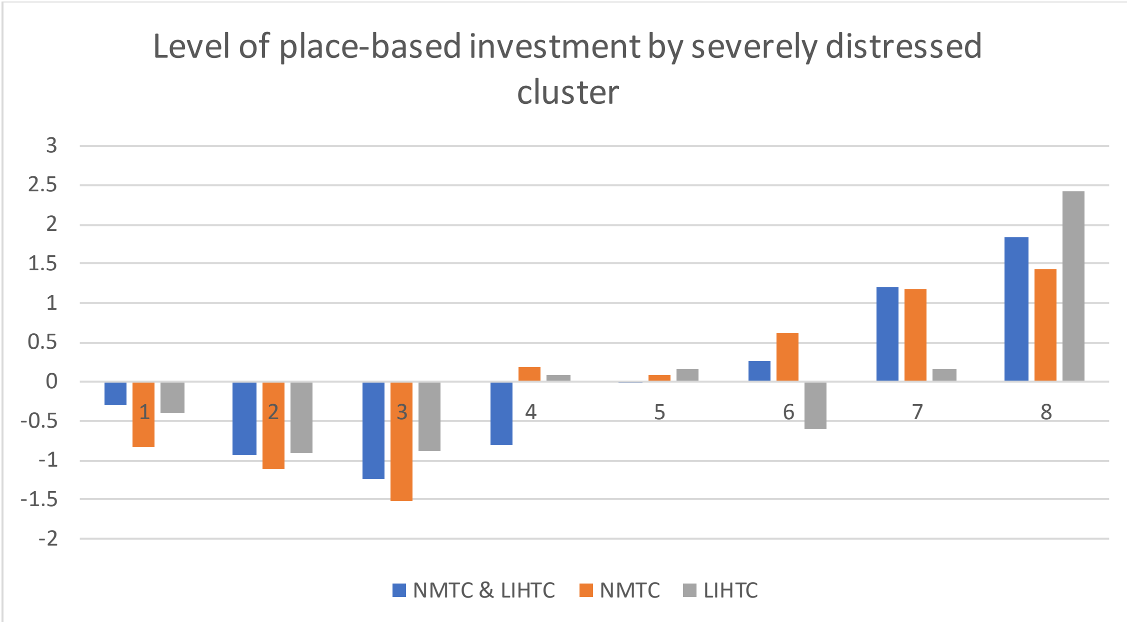

Figure 19. NMTC & LIHTC Investment by Severely distressed Cluster

The urbanization dimension was significantly positively correlated with all five measures of 2000 to 2009-2013 socioeconomic change, as well as with all three measures of place-based investment (percent of tracts that received (a) NMTC, (b) LIHTC, and (c) NMTC and LIHTC). In other words, higher scores on the urbanization index were associated with both socioeconomic ascent and higher levels of place-based investment.

There was also a significant association between higher scores on the black isolation index and declines in 2000 to 2009-2013 poverty. The two neighborhood clusters with the highest average scores on the black isolation index also had the highest initial poverty rates of all the severely distressed clusters. Thus, it is possible that this association may reflect encouraging gains made within the poorest and most racially isolated neighborhood types; alternatively, it is also possibly a ceiling effect of sorts. There were no significant correlations with either of the other two neighborhood dimensions. Furthermore, the observed neighborhood attributes associated with urbanization, such as percent owner-occupied homes, percent of housing in multi-unit structures, and population density, were all significantly correlated with most or all socioeconomic change measures, as well as NMTC/LIHTC investment measures. Only a few other observed neighborhood variables that were unrelated to urbanization were correlated with single measures of socioeconomic change or NMTC/LIHTC investment.

Thus, it appears that the preferences of developers seeking locations for NMTC and LIHTC-subsidized development were in large part a function of how urbanized an area was.

3.7 Discussion & Conclusions

This study has several important theoretical and applied policymaking implications. First, the two neighborhood typologies that were identified, one containing both moderate-distress and severely distressed census tracts, and the other focused on severely distresseded census tracts alone, underscore the reality that the consequences of concentrated poverty are a problem facing a diverse range of places and populations. The classification of poor census tracts according to their levels of socioeconomic distress, urbanization, and black isolation revealed the existence of several distinct types of poor places that exist throughout the metropolitan landscape from the inner cities to the outlying suburbs, and that are home to populations of all variety of demographic backgrounds.

Second, while calls to recognize the problem of suburban poverty have gotten louder and more frequent in recent years, the finding that urbanization was a primary driver of both socioeconomic ascent and multiple forms of place-based investment highlights the challenges that distressed neighborhoods in the suburbs must confront. The current popularity of market-based solutions that tend to favor more densely populated areas suggests the need for policy solutions that specifically address the issue of suburban poverty, which is still too often overlooked.

Third, the finding that NMTC and LIHTC investment patterns closely mirrored one another across the different neighborhood types justifies two of the primary concerns that motivated this dissertation. The first is that the preferences of developers, who play a key role in determining where NMTC and LIHTC-subsidized projects are located, have not been studied in depth, leading to uncertainty in evaluations of program impact that treatment selection has been fully and adequately specified. Given the similar mechanisms through which NMTC and LIHTC resources are delivered into poor neighborhoods, the parallel locational patterns of NMTC and LIHTC investment are likely driven by a common underlying force. Although they have never been examined together, previous studies of both programs independently suggest that this force is related to the preferences of developers.

The analysis found that neighborhood attributes relating to the level of urbanization, moderated by program provisions that favor investment in severely distressed over moderate-distress areas, largely accounted for the locational patterns of both NMTC and LIHTC investment. Thus, this study offers the clearest image yet of the preference structure of market actors involved in programs like NMTC and LIHTC. Ensuring that census tracts that received either NMTC or LIHTC investment had identical pre-treatment levels of urbanization as those selected to provide the counterfactual addresses this model's misspecification concern, which has been independently raised in previous studies of both programs.

The second concern motivating this dissertation is that, due to their underlying similarities, evaluating the impact of either program on neighborhood conditions will lead to biased estimates if the presence of the other program in similar kinds of poor places is not taken into account. The neighborhood types identified through the cluster analysis are defined by their similar configurations along three complex, underlying neighborhood dimensions. That such strong parallels in NMTC and LIHTC investment patterns were observed in this complex setting suggests this concern is not unfounded.

CHAPTER 4

THE EFFECTS OF NMTC AND LIHTC INVESTMENT ON LOCAL SOCIOECONOMIC CONDITITIONS

4.1 Introduction

The previous chapter revealed important clues about the underlying links between the different types of poor neighborhoods and the locational patterns of place-based investment. It found that the neighborhood types that experienced the strongest and most consistent socioeconomic improvement from 2000 to 2009-2013 also attracted higher concentrations of investment through both NMTC and LIHTC. This lends support for the assumption made in previous research on both programs that developers seek out locations that they expect will improve over time.

The previous chapter also found that the neighborhood dimension describing the degree of urbanization in a census tract in 2000 was correlated with subsequent NMTC investment, LIHTC investment, and multiple indicators of neighborhood socioeconomic change. No other neighborhood dimension or individual observed attribute was consistently related with both types of place-based investment and also socioeconomic change. This suggests that the urbanization dimension uncovered through principal components analysis may serve as a close approximation of the latent construct of "developer preferences." The only caveat to this is that among the highly urbanized neighborhood types identified, those that were only moderately distressed in 2000 received less investment through NMTC and LIHTC than those that had higher initial levels of socioeconomic distress. Thus, while developers have the most direct influence on where NMTC- and LIHTC-subsidized projects are located, their preferences may be moderated by program provisions that encourage development in areas with lower income and higher poverty rates than the basic eligibility requirements dictate.

The current chapter investigates the effects of NMTC investment and LIHTC investment on socioeconomic outcomes in distressed neighborhoods. The insights from the previous chapter regarding the underlying processes driving NMTC and LIHTC site selection are applied to the development of a quasiexperimental model that addresses a methodological issue that has haunted previous evaluations: the potential for model misspecification due to the unobserved preferences of developers for certain types of poor places.

For both NMTC and LIHTC, it was found that the urbanization dimension was the primary underlying driver of site selection. In an evaluation focused on either NMTC or LIHTC, taking extra care to ensure the pretreatment similarity of treated and comparison census tracts on this dimension, or at least on the observed attributes associated with it, such as homeownership rates, proportion of single family housing, population density, and home values, would go a long way to bolstering confidence in estimates of program impact.

However, this same finding, that NMTC and LIHTC site selection appears to be driven by the same underlying process, raises a new methodological question that has never before been considered: given the parallels in the neighborhood attributes that attract NMTC and LIHTC investment, does evaluating one program without controlling for the presence of the other result in biased estimates of program impact?

The similarities in NMTC and LIHTC investment patterns within and across neighborhood types are not just superficial, given that the neighborhood clusters were identified by their similarities across three complex unobserved neighborhood dimensions. Thus, even if a reasonably good job is done of properly specifying site selection in an evaluation of one program or the other, there remains the distinct possibility that the group of treated tracts were more likely than the comparison group to have been targeted by the program that is not the focus of the evaluation.

Omitting an important explanatory variable from a model is a concern regardless of the direction in which estimates are biased. However, the issue takes on an interesting twist in the current study, considering the controversy surrounding LIHTC's place-based provisions, which provide developers with additional incentives to locate affordable housing development specifically in places that are already disproportionately poor. As a consequence, there is evidence that at least in some neighborhood contexts, LIHTC-subsidized development exacerbates existing patterns of concentrated poverty or otherwise has a negative impact on indicators neighborhood socioeconomic well-being. In contrast, there is little debate that the worst-case scenario for NMTC would be a finding that it is a non-factor in efforts to revitalize distressed neighborhoods.

Assuming for the moment that the overall effect of LIHTC-subsidized housing development in poor neighborhoods is to push the socioeconomic trajectory of targeted areas downward, then an omitted LIHTC variable in an evaluation focused on NMTC would effectively cancel out some of the true positive socioeconomic gains attributable to NMTC. In an evaluation focused on LIHTC, the unaccounted-for revitalizing effects of

NMTC development would similarly mask some of the poverty-concentrating effects of LIHTC.

The current chapter proposes an evaluation approach that embraces the unique relationship between NMTC and LIHTC. The insights gained from the previous chapter regarding the underlying neighborhood factors that drive both NMTC and LIHTC site selection are applied to several counterfactual models that attempt to estimate the socioeconomic changes a distressed census tract would have experienced from 2000 to 2009-2013 if it had received no place-based investment, or if it had received some combination of NMTC/LIHTC investment other than the treatment combination that it did receive. In total, NMTC and LIHTC treatment effects are examined through the six models shown in 17, along with the predicted differences in outcomes for each set of treatment and comparison census tracts.

Table 17. Treatment-comparison models and predicted effect of treatment

Model	Treatment	Comparison	Treatment effect
1	NMTC and LIHTC	NMTC only	-
2	NMTC and LIHTC	LIHTC only	+
3	NMTC and LIHTC	Neither	No difference
4	NMTC only	LIHTC only	+
5	NMTC only	Neither	+
6	LIHTC only	Neither	-

While questions remain as to whether LIHTC-subsidized housing development helps or hurts low-income communities, the hypotheses continue with the assumption that the poverty-concentrating effects of LIHTC outweigh its potential to revitalize distressed areas. Thus, model 1 predicts that a census tract that received only NMTC investment would have experienced worse socioeconomic outcomes if it had instead received both NMTC and LIHTC investment. Model 2 predicts that the injection of NMTC investment into a census tract that only received LIHTC would have the opposite effect, producing improved socioeconomic outcomes. Model 3 predicts that the positive externalities generated by NMTC investment are effectively cancelled out by the poverty concentrating effects of LIHTC. Thus, a census tract that received no form of place-based treatment would have experienced the same socioeconomic outcomes if it had instead been targeted by both NMTC and LIHTC. Model 4 predicts that if a census tract that received LIHTC investment had instead received NMTC investment, it would have experienced better socioeconomic outcomes. Models 5 and 6 represent the typical evaluation design that estimates the treatment effects of a single program against the counterfactual of no treatment. When compared to low-income census tracts not targeted by either program, model 5 predicts that NMTC investment improves socioeconomic outcomes, while model 6 predicts that LIHTC continues to demonstrate a negative impact on indicators of socioeconomic well-being.

4.2 Methods

4.2.1 Define Program Treatment

In the previous chapter, program treatment was defined in binary terms, requiring only that some nonzero amount of investment had been received. That simple operationalization was sufficient, as the primary concern was with the locations of NMTC- and LIHTC-subsidized projects. In the current chapter, the goal is to estimate the socioeconomic effects of those investments. Recognizing that bigger investments would generally be expected to yield more significant local changes, a more comprehensive operational definition of program treatment was needed to accomplish the goals of this evaluation.

Research on a different place-based program, the Community Development Block Grant (CDBG) program, offers some insight for defining program treatment. Galster and colleagues (Galster, Tatian, & Accordino, 2006; Galster, Walker, Hayes, Boxall, & Johnson, 2004) found that CDBG spending in a census tract above the mean level of spending for all census tracts in the same metropolitan area represented an important threshold of investment, above which significant improvements in neighborhood conditions were realized. Unfortunately, there were quite a few metropolitan areas in the current study in which only one or two census tracts received NMTC or LIHTC investment. In these cases, the mean level of metropolitan spending obviously cannot serve as a meaningful investment threshold. Still, I thought it important to impose some minimum program treatment threshold. Because the literature on NMTC and LIHTC provides no relevant guidance, a relatively lenient figure of $100,000 was selected for this purpose. There were 91 census tracts that from 2003 to 2007 received nonzero amounts of NMTC or LIHTC investment less than $100,000. They were eliminated from further analysis.

Of the 14,659 census tracts that remained, 2,332, or approximately 16 percent, received some form of place-based investment between 2003 and 2007. There were 734 that received NMTC investment and 1,764 that received LIHTC. While most census tracts were targeted by only one program or the other, 166 were targeted by both NMTC and LIHTC. This small, yet not insignificant subset of distressed census tracts that received investment through both programs suggests the delineation of three distinct categories of place-based treatment, as it was possible for a census tract to have been targeted by (a) NMTC alone, (b) LIHTC alone, or (c) by both NMTC and LIHTC.

4.2.2 Generate Propensity Scores

Propensity score matching (PSM) is an approach for making causal claims in observational studies when random assignment into treatment and control groups is not possible. It is a multi-step process that begins with the assignment of a "propensity score" to all observations in a data set. In general, the propensity score is calculated by regressing a dummy treatment variable onto a set of pretreatment attributes using logistic regression or another model appropriate for dichotomous dependent variables. The fitted value for each observation is interpreted as its predicted probability of receiving the treatment given its pretreatment characteristics. This value, which ranges from 0 to 1, is its propensity score.

The propensity score of each treated observation is then compared to the propensity scores from a pool of untreated observations. The goal of the matching procedure is, for each treated observation, to identify one or more corresponding untreated observations with identical propensity scores. All untreated observations without propensity scores identical to any of the treated observations are removed from the comparison pool. Similarly, any treated observations for which there are no suitable comparisons may also be excluded from analysis. What remains is a matched sample of observations that had the same predicted probability of receiving the treatment given a set of pretreatment characteristics. If all relevant pretreatment factors related to treatment selection were included in the matching procedure, and there were suitable comparison observations to be found for most or all of the treated ones, the only relevant difference between the treatment and comparison groups should be the treatment itself (Ho et al., 2007).

Because there are multiple treatment conditions in this study, a modification of the typical approach to PSM was necessary. Using methods developed and validated by Lechner (2001, 2002) for simultaneously calculating the predicted probabilities that an observation will receive each of multiple potential treatments, I coded a variable that placed each census tract into one of four mutually exclusive treatment groups. Based on the definition of program treatment described above, the variable reflected whether a census tract received above-threshold levels of investment through (a) both NMTC and LIHTC; (b) NMTC only; (c) LIHTC only; or (d) neither NMTC nor LIHTC. This treatment combination variable, *treat.combo,* then served as the dependent variable in the following multinomial logit regression:

treat.combo = mfi.ratio.00 + poverty.pct.00 + own.pct.00 + homes_multi_unit.pct.00 + unemp.pct.00 + density.00.ratio + mhmval.00.ratio + black.pct.00 + other.race.00+ mhmval.90ch + urbanization

Where

- mfi.ratio.00 = MFI ratio in 2000
- poverty.pct.00 = poverty rate
- own.pct.00 = percent of housing units that were owner-occupied
- homes_multi_unit.pct.00 = percent of housing units located in multi-unit structures
- unemp.pct.00 = unemployment rate
- density.00.ratio = population density in census tract / metropolitan area
- mhmval.00.ratio = median home value in census tract / metropolitan area
- black.pct.00 = percent black
- other.race.00 = percent neither non-Hispanic black nor non-Hispanic white
- mhmval.90ch = mhmval.00.ratio – mhmval.90.ratio

- urbanization = component score for urbanization dimension identified through PCA

The validity of estimates generated through PSM depend on the specification of a matching model that fully and properly accounts for "all variables that affect both the treatment assignment and, controlling for the treatment, the dependent variable (Ho et al., 2007)." If important variables are not included in the matching process, or if the matching criteria are not sufficiently strict for key variables, then significant bias can be introduced into the model, making it impossible to confidently attribute observed differences between treated and untreated groups to the effects of the treatment (Ho et al., 2007). To meet the requirements for causal validity, the matching model in the current study must therefore include the neighborhood attributes of census tracts in 2000 that affected both (a) its chances of being selected for NMTC and/or LIHTC during the 2000s, and (b) its 2000 to 2009-2013 socioeconomic trajectory.

Thus, the independent variables included in the regression equation were selected to provide a well-rounded view of distressed census tracts eligible for NMTC and LIHTC at a point in time shortly before treatment assignment occurred. Care was taken to include variables that the findings from the previous chapter, as well as evidence from other sources, suggest would have figured prominently in the decision-making process of developers.

The only variables requiring any further explanation are perhaps *urbanization* and *mhmval.90ch*. The variable *urbanization* is an index of the urbanization dimension identified by PCA in the previous chapter (the composition of this index is shown in Table 3 under the column *TC2*). It was found to be closely related to patterns of both

NMTC/LIHTC investment and neighborhood socioeconomic change. Consequently, the weighted combination of pretreatment neighborhood attributes contained within this index were determined to bear close resemblance to the latent construct of "developer preferences," which previous studies have identified as an important, yet unobserved driver of treatment selection. Though the observed variables that this index most strongly relates to are also included in the model in their original uncombined forms, there is a potential benefit to including them in their combined form as well, as Jakubowski (2014) finds that matching observations on latent variables may yield estimates with smaller standard errors.

The variable *mhmval.90ch* represents the change in rank in the median home value of a census tract from 1990 to 2000, within its metropolitan area. Thus, census tracts with values greater than 1 on this variable experienced housing appreciation that outpaced the metropolitan area average in the decade leading up to the study baseline. Baum-Snow and Marion (2009) used a similar variable to represent recent gentrification in an evaluation of LIHTC, and found that it related to both the locations and effects of future LIHTC investment. Furthermore, all the other independent variables describe the static attributes of census tracts in 2000. Given that neighborhoods are constantly changing and evolving, it was important to include at least one dynamic measure to represent a census tract's recent history and socioeconomic trajectory as of 2000.

Instead of a single propensity score, four separate propensity scores were generated to represent the predicted probabilities of receiving each of the treatment combinations. Table 18 summarizes the predicted probabilities for each of the four treatment categories.

Table 18. Predicted Probabilities of Receiving each Treatment (%)

Treatment	Mean	Minimum	Maximum
NMTC and LIHTC	1.13	0.00	25.09
NMTC only	3.87	0.02	24.47
LIHTC only	10.90	0.42	43.64
Neither	84.09	31.93	99.55

4.2.3 Match Treatment-Comparison Subsets

The matching procedure was performed using the *R* package *Matching*. First, the data was split into six subsets of census tracts, corresponding to the treatment and comparison groups outlined in Table 20. The following steps were performed on each subset of the data.

For each census tract in the treatment group, the pool of potential matches was restricted to those comparison tracts that were classified into the same neighborhood type in Chapter 3. One-to-one matching was used, meaning that each treated census tract was paired with the census tract from the comparison pool with smallest difference in propensity score. Census tracts were only considered matches if their propensity scores were within .25 standard deviations of each other. Thus, all census tracts from the treatment group that could not be matched with a sufficiently similar comparison tract were discarded.

What results is a dataset containing an equal number of treated and comparison observations. If the matching procedure was successful, the pretreatment characteristics of the treatment and comparison groups should be indistinguishable. There is no single metric or rule for determining if a matched dataset is sufficiently balanced. Rather, the user should employ multiple diagnostic tools to make that judgement (Ho et al., 2007). The appendix provides the differences in the mean values of each treatment-comparison group before and after the matching procedure was performed.

4.2.4 Estimate Treatment Effects

The final step was to estimate the effects receiving one combination of NMTC/LIHTC treatment, relative to either a different NMTC/LIHTC treatment combination or no treatment. Difference-in-difference estimates were obtained for the six counterfactual models on four socioeconomic outcomes: 2000 to 2009-2013 change in (a) log of median family income, (b) unemployment, (d) poverty, and (e) log of median home value. The DD estimates for the counterfactual models were obtained through the following equations:

Model 1: NMTC and LIHTC versus NMTC alone:

$$Y = \beta_0 + \beta_1 \mathit{both\_dum} + \beta_2 \mathit{NMTC\_amt} + \beta_3 \mathit{controls} + \beta_4 \mathit{black10} + \beta_5 \mathit{County} + \varepsilon$$

Model 2: NMTC and LIHTC versus LIHTC alone:

$$Y = \beta_0 + \beta_1 \mathit{both\_dum} + \beta_2 \mathit{LIHTC\_amt} + \beta_3 \mathit{controls} + \beta_4 \mathit{black10} + \beta_5 \mathit{County} + \varepsilon$$

Model 3: NMTC and LIHTC versus neither:

$$Y = \beta_0 + \beta_1 \mathit{both\_dum} + \beta_2 \mathit{controls} + \beta_3 \mathit{black10} + \beta_4 \mathit{County} + \varepsilon$$

Model 4: NMTC only versus LIHTC only:

$$Y = \beta_0 + \beta_1 \mathit{NMTC\_dum} + \beta_2 \mathit{controls} + \beta_3 \mathit{black10} + \beta_4 \mathit{County} + \varepsilon$$

Model 5: NMTC only versus neither

$$Y = \beta_0 + \beta_1 \mathit{NMTC\_dum} + \beta_2 \mathit{controls} + \beta_3 \mathit{black10} + \beta_4 \mathit{County} + \varepsilon$$

Model 6: LIHTC only versus neither:

$$Y = \beta_0 + \beta_1 \mathit{LIHTC\_dum} + \beta_2 \mathit{controls} + \beta_3 \mathit{black10} + \beta_4 \mathit{County} + \varepsilon,$$

Where Y represents the four socioeconomic outcomes listed above, and the variables *both_dum*, *NMTC_dum*, and *LIHTC_dum* are dummy variables coded to one if a census tract received the treatment condition, and zero if it received the comparison condition. Thus, the models estimate the effects of receiving some above-threshold (>$100,000) amount of investment through both programs (Models 1-3), NMTC (Model 4 & 5), or LIHTC (Model 6), relative to the comparison condition.

The makeup of the comparison groups in models 1 and 2 necessitated the inclusion of the variables *NMTC_amt* and *LIHTC_amt* to account for the dollar amount of investment received by the comparison group through NMTC (model 1) and LIHTC (model 2). In model 1, both the treatment and comparison groups received investment through NMTC. In model 2, both groups received LIHTC. Ideally, I would have matched the census tracts in the treatment group to comparison census tracts that received similar amounts of investment through NMTC (model 1) or LIHTC (model 2). Unfortunately, investment amounts for both programs varied widely from tract to tract, and were uncorrelated with the other pretreatment attributes used to calculate the propensity scores. As a result, attempts to include measures of NMTC and LIHTC investment amounts in the matching procedures threw off the balance between the treatment and comparison groups on other important pretreatment variables. Thus, it was necessary to control for differences in investment intensity at this stage. If *NMTC_amt* and *LIHTC_amt* were not included in the equations for models 1 and 2, then observed differences in the outcomes of the treatment and comparison groups might be explained more by large differences in the amount of investment received by the treatment and comparison groups through the program that both groups received than by the addition of investment through the program that only the treatment group received.

The variable *controls* includes the eleven variables listed earlier used to obtain the propensity scores. Because it is rarely the case that propensity scores produce exact matches for all observations on all relevant variables, including these variables in the final regression equations accounts for any remaining differences between the treatment and comparison observations. Two additional control variables were included, *black10* and *County*.

First, *black10* is the percentage point change in the black population from 2000 to 2009-2013. Recent research demonstrates that the process of neighborhood socioeconomic ascent may occur through one or more of several distinct pathways (Owens, 2012; Van Criekingen & Decroly, 2003). In the context of concentrated poverty, the most well-known of these pathways is the classic gentrification process in which ascent occurs through the displacement of the traditional, often minority residents of a distressed neighborhood by wealthier, and typically white newcomers. Given that one of the criticisms of place-based investment is that resources are often siphoned off by unintended beneficiaries before they are able to reach the intended beneficiaries (Crane & Manville, 2008; Glaeser & Gottlieb, 2008; Gurley-Calvez et al., 2009)- i.e., the current residents of targeted areas, it is important to distinguish between different pathways of ascent. The purpose of the variable *black10* is to control for improved socioeconomic conditions in poor neighborhoods resulting from the displacement of current residents.

Second, the factor variable *County* controls for county fixed effects. A neighborhood's socioeconomic trajectory is a function of the changes it experiences directly, such as those that result from NMTC or LIHTC investment, as well as the social, political, geographic, and economic realities of the surrounding area (Galster, 2001). Thus, it was important to control for potentially vast regional differences that are consequential for socioeconomic outcomes.

4.3 Results

The quality of the matches in the six counterfactual models was assessed using the best practices suggested by Ho, Imai, and King (Ho et al., 2007); adjustments were made to the specification of the matching model until a combination of variables was identified that produced good balance on key pretreatment variables for all six treatment-comparison groups. The tables in the appendix provide descriptive statistics for the counterfactual models before and after matching. T-tests were also performed to establish that the differences between the matched treatment and comparison groups were insignificant. In this respect, the matching procedure was unable to remove all significant differences on all variables in some of the models; however, these remaining differences were for the most part inconsequential in a practical sense. For example, before conducting the matching procedure for counterfactual model 1 (treatment: both NMTC and LIHTC; comparison: NMTC only), the mean poverty rates of the treatment and comparison groups were 30.5 percent and 25.3 percent, respectively. Though the matching procedure eliminated more than half of the original distance between the groups (new mean poverty rates of 27.2 percent for treatment group and 25.1 percent for comparison group), the t-test still indicated that the two groups were significantly different on this important pretreatment attribute. However, there is little substantive difference between a census tract with a poverty rate of 27.2 percent and one with a poverty rate of 25.1, in terms of either NMTC or LIHTC provisions, developer preferences, likely socioeconomic trajectory, or the ability of an observer to detect the differences. Furthermore, the inclusion of year 2000 poverty rate in the final regression equation cancels out this remaining imbalance. The empirical results are presented from Table 19 to Table 24.

Table 19 estimates the differences in socioeconomic outcomes between census tracts that received only NMTC investment and those that received the same amount of NMTC investment plus some above-threshold (>$100,000) amount of LIHTC investment. It finds that the addition of LIHTC-subsidized housing had no significant impact in either direction on the socioeconomic outcomes of census tracts that were targeted by NMTC alone.

However, the significant NMTC spending coefficient on the equation looking at 2000 to 2009-2013 unemployment change indicates that every $100,000 of NMTC investment reduced unemployment change by .006 percentage points, regardless of whether LIHTC was received. On average, unemployment rose in this sample by 2.01 percent. Given that the average NMTC investment amount was $9.5 million, unemployment would have risen by an additional .57 percentage points (.006 * 95) over the course of the 2000s were it not for NMTC spillovers.

Table 19. Treatment Effects Both vs. NMTC

	Dependent variable:			
	MFI	Poverty	Unemployment	Home Values
Treatment:NMTC and LIHTC	0.040	-0.352	0.436	-0.006
	(0.045)	(1.316)	(0.827)	(0.046)
NMTC (per $100,000)	0.0001	-0.001	-0.006**	0.0001
	(0.0001)	(0.003)	(0.002)	(0.0001)
Constant	-0.743*	60.790***	24.175***	-0.022
	(0.413)	(12.149)	(7.635)	(0.423)
Observations	308	308	308	308
R^2	0.666	0.707	0.808	0.697
Adjusted R^2	0.401	0.474	0.655	0.455
Residual Std. Error (df = 171)	0.261	7.683	4.828	0.268
F Statistic (df = 136; 171)	2.508***	3.030***	5.282***	2.886***
Note:			*p<0.1, **p<.05, ***p<0.01	

Table 20 estimates the differences in socioeconomic outcomes for census tracts that received only LIHTC investment and those that received the same amount of LIHTC investment plus some above-threshold level of NMTC investment. It finds that the injection of NMTC-subsidized development yielded improved outcomes in poverty rate change. This finding supports the hypothesis that NMTC-subsidized development improves socioeconomic outcomes in distressed neighborhoods. On the other hand, it does not necessarily say anything about the effects of LIHTC investment. After controlling for NMTC investment and other relevant neighborhood factors, increasing amounts of LIHTC spending had no significant influence on census tract socioeconomic change in this sample.

Table 20. Treatment Effects Both vs. LIHTC

	Dependent variable:			
	MFI	Poverty	Unemployment	Home Values
Treatment:NMTC and LIHTC	0.040	-3.824^{***}	-0.586	0.040
	(0.043)	(1.132)	(0.807)	(0.051)
LIHTC (per $100,000)	0.0001	-0.033	0.035	-0.001
	(0.002)	(0.057)	(0.041)	(0.003)
Constant	-0.225	37.689^{***}	25.080^{***}	0.471
	(0.298)	(7.795)	(5.556)	(0.351)
Observations	316	316	316	316
R^2	0.690	0.698	0.783	0.633
Adjusted R^2	0.425	0.440	0.598	0.321
Residual Std. Error (df = 170)	0.273	7.149	5.096	0.322
F Statistic (df = 145; 170)	2.606^{***}	2.707^{***}	4.235^{***}	2.025^{***}
Note:				*p<0.1, **p<.05, ***p<0.01

Table 21 estimates the differences in outcomes for census tracts that received above-threshold amounts of investment through both NMTC and LIHTC, compared to otherwise comparable census tracts that were not targeted by either program. In this scenario, it was found that being targeted by both programs had a positive impact on both income and poverty outcomes. While my original prediction was that the revitalizing effects of NMTC investment would be canceled out by the poverty concentrating effects of LIHTC investment, it may instead be the case that NMTC and LIHTC together created a critical mass of new investment that catalyzed the revitalization process. Another possibility is that because the average amount of NMTC investment received by the treatment group was considerably higher than LIHTC (NMTC: $11.1 million; LIHTC: $955,000), the positive effects of NMTC outweighed any negative effects of LIHTC investment.

Table 21. Treatment Effects Both vs. Neither

	Dependent variable:			
	MFI	Poverty	Unemployment	Home Values
Treatment:NMTC and LIHTC	0.113*	-3.745**	-0.852	0.005
	(0.059)	(1.655)	(0.883)	(0.054)
Constant	-1.186**	57.797***	33.974***	0.921**
	(0.474)	(13.203)	(7.041)	(0.428)
Observations	326	326	326	326
R^2	0.627	0.599	0.813	0.675
Adjusted R^2	0.286	0.234	0.643	0.378
Residual Std. Error (df = 170)	0.328	9.140	4.874	0.297
F Statistic (df = 155; 170)	1.840***	1.642***	4.771***	2.276***
Note:				*p<0.1, **p<.05, ***p<0.01

Table 22 considers what would have happened if a census tract that received above-threshold LIHTC investment had instead receive above-threshold NMTC investment. This counterfactual finds that replacing LIHTC with NMTC had significant benefits for both income and home value change.

Table 22. Treatment Effects NMTC vs. LIHTC

	Dependent variable:			
	MFI	Poverty	Unemployment	Home Values
Treatment: NMTC Only	0.075***	-0.087	-0.508	0.049**
	(0.024)	(0.701)	(0.479)	(0.024)
Constant	-0.506**	51.144***	20.601***	0.245
	(0.216)	(6.395)	(4.368)	(0.217)

Observations	1,104	1,104	1,104	1,104
R^2	0.491	0.539	0.687	0.560
Adjusted R^2	0.284	0.351	0.559	0.381
Residual Std. Error (df = 784)	0.279	8.282	5.657	0.282
F Statistic (df = 319; 784)	2.373***	2.869***	5.388***	3.126***
Note:				*p<0.1, **p<.05, ***p<0.01

Table 23 and Table 24 show the effects of receiving above-threshold amounts of NMTC and LIHTC investment, respectively, relative to the counterfactual condition of receiving no investment through either program. Table 23 finds that home values rose more in census tracts that received NMTC, while Table 24 finds that LIHTC investment was responsible for weaker income growth and a sharper increase in poverty.

Table 23. Treatment Effects NMTC vs. Neither

	Dependent variable:			
	MFI	Poverty	Unemployment	Home Values
Treatment:NMTC Only	-0.007	0.075	-0.544	0.050**
	(0.022)	(0.688)	(0.423)	(0.021)
Constant	-0.376	46.529***	28.485***	0.225
	(0.246)	(7.531)	(4.629)	(0.234)
Observations	1,128	1,128	1,128	1,128
R^2	0.464	0.453	0.649	0.577
Adjusted R^2	0.255	0.241	0.513	0.412
Residual Std. Error (df = 811)	0.286	8.752	5.380	0.272
F Statistic (df = 316; 811)	2.219***	2.129***	4.751***	3.499***
Note:				*p<0.1, **p<.05, ***p<0.01

Table 24. Treatment Effects LIHTC vs. Neither

	Dependent variable:			
	MFI	Poverty	Unemployment	Home Values
Treatment:LIHTC Only	-0.022**	0.643*	0.027	0.004
	(0.010)	(0.350)	(0.257)	(0.011)
Constant	-0.067	39.343***	21.766***	0.258
	(0.195)	(6.523)	(4.799)	(0.196)
Observations	3,192	3,192	3,192	3,192
R^2	0.395	0.436	0.549	0.546
Adjusted R^2	0.282	0.331	0.465	0.461
Residual Std. Error (df = 2690)	0.253	8.469	6.230	0.255
F Statistic (df = 501; 2690)	3.500***	4.152***	6.532***	6.448***
Note:				*p**p***p<0.01

4.4 Discussion

This chapter investigated the effects of being targeted by either NMTC or LIHTC in census tracts that otherwise received investment through the other program or that were targeted by neither NMTC nor LIHTC, on the socioeconomic trajectories of distressed places.

In the only similar study on NMTC to date, Freedman (2012) found that NMTC eligibility had modest positive impacts on income and poverty change. This study supports those earlier findings, as in three of the four counterfactual scenarios where the treatment involved the addition of NMTC investment into a census tract, change in the desired direction was observed for one or both of these indicators. The current study is also the first to find evidence of NMTC investment's positive impacts on local home values. Of the four indicators investigated, the only one for which NMTC was not found to have any significant impact was change in the unemployment rate.

The findings tell a more nuanced story about the socioeconomic effects of LIHTC investment. In three of the models, the treatment involved LIHTC investment in a census tract. In the scenario where LIHTC investment was an addition to NMTC investment (Table 22), LIHTC was found to have no significant impact on socioeconomic change. When LIHTC investment occurred in conjunction with NMTC investment in places that were otherwise not targeted by either program, positive socioeconomic changes were observed. When the counterfactual condition involved no place-based treatment, the addition of LIHTC investment led to worse outcomes in terms of both income and poverty. In other words, there were contexts in which the implications of LIHTC investment in a poor neighborhood were negligible, positive, and negative.

CHAPTER 5

CONCLUSIONS

5.1 Summary of Findings

This dissertation explored the various poverty contexts that place-based programs like NMTC and LIHTC are tasked to address, identified the neighborhood attributes most important for determining whether a distressed census tract is likely to be targeted for place-based investment, and estimated the effects of those investments on local socioeconomic conditions with the understanding that different sources of place-based investment may gravitate towards the same kinds of distressed places.

Chapter 3 found that local levels of human capital and distress, urbanization, and the degree to which the populations of poor neighborhoods are racially segregated are the three neighborhood dimensions that are the main sources of variation among poor places. The cluster analysis delineated distressed census tracts according to these dimensions and revealed the existence of ten distinct and interpretable types of poor neighborhoods. The neighborhood types with the highest concentrations of census tracts that received NMTC and LIHTC investment were those that experienced the best socioeconomic outcomes during the 2000s. This finding supports the assumptions made in previous research on both programs that developers seek out distressed places that are well-positioned to experience socioeconomic ascent.

A census tract’s initial level of urbanization was strongly associated both with subsequent socioeconomic change and subsequent place-based investment through NMTC and LIHTC. No other observed attribute or dimension was related to these processes. Therefore, urbanization, which in this study refers to a combination of population, housing, and proximity features, including low levels of homeownership, a high proportion of housing in apartments and other multi-unit structures, low relative income, high relative home values values, and high relative population density, is likely to be closely related to the latent construct of "developer preferences," and thus an important determinant of treatment selection.

With a deeper understanding of the unobserved treatment selection processes that steer NMTC and LIHTC into similar types of distressed places, Chapter 4 estimated the effects of investments made through these programs in their shared space. Six counterfactual models were examined, each of which examined the effects of adding either NMTC or LIHTC investment into a census tract that received the other program or that was not targeted by either program. In every case where the treatment involved the addition of NMTC investment in a census tract, there was evidence of socioeconomic gains on at least one indicator. In contrast, increased poverty and lower income were observed when LIHTC investment was the treatment. The only exception to this was the model that compared the effects of receiving both NMTC and LIHTC treatment to no treatment through either program. In this case, being targeted by both programs had significant benefits in terms of both poverty and income change.

5.2 Limitations of Study

This research ran up against two main limitations, both related to the data used to represent neighborhoods. Neighborhood is a complex, multifaceted concept, and there was simply no way to build neighborhood profiles using available tract-level data that incorporated every important aspect of a neighborhood's being. Because this study looked at areas of socioeconomic distress in metropolitan areas throughout the US, I was limited to using universally available census tract data. While Galster (Galster, 2001) identifies at least ten distinct types of neighborhood attributes, I conceptualized neighborhoods around the four attribute types for which suitable indicators were readily available- demographic, class status, housing, and relative location/proximity characteristics. However, these sorts of data limitations are all but unavoidable in neighborhood research, particularly in a geographically expansive study such as this.

Still, dozens of tract-level variables are available through the census, and it is possible to construct dozens more through various combinations and permutations. Despite the availability of many more variables for describing neighborhood attributes, I selected 13 neighborhood variables for inclusion in the PCA. By comparison, using the same two-step approach to develop a typology of inner-ring suburban census tracts, Hanlon (Hanlon, 2009) entered 44 variables into PCA to uncover neighborhood dimensions. However, I found that PCA was most successful at producing coherent neighborhood dimensions with a limited set of theoretically relevant indicators. After dozens of iterations, I found that the 13 variables included in the PCA struck a strong balance between comprehensiveness and coherence.

On the other hand, there is certainly room to argue that I left some key pieces of information relevant for understanding neighborhood socioeconomic trajectories on the table. Specifically, the included variables are all static indicators of a census tract's characteristics at a specific point in time. I did not include any dynamic variables representing the recent history and trajectory leading up to the start of the study period in 2000. This is a legitimate concern because neighborhood typologies often incorporate dynamic measures, and several recent typologies have focused on the evolution of neighborhood structure and the pathways of socioeconomic ascent over the course of decades (Delmelle, 2015, 2017; Owens, 2012).

I originally intended to include 1990-2000 change in home value as one of the variables for identifying neighborhood dimensions, as previous research suggests that the direction in which LIHTC pushes socioeconomic outcomes may depend on whether a census tract was ascending, stable, or declining at the time of the investment (Baum-Snow & Marion, 2009). However, this change variable was not sufficiently correlated with any of the static year 2000 variables. As a result, when it was included in the PCA it tended to load highly on a component by itself, muddying its interpretation and limiting its usefulness as a meaningful neighborhood dimension. When that failed, I tried to instead include it in the cluster analysis, alongside with the three meaningful dimensions that were identified. Again, its inclusion made the interpretation of distinct and meaningful neighborhood types difficult. Thus, I settled for using it as one of the matching variables in the second empirical chapter. In the end, the set of static variables for this study produced interpretable and theory-backed neighborhood dimensions and neighborhood types. Furthermore, ensuring that treated and comparison tracts had similar trajectories leading up to the treatment selection period is the most important use of this dynamic variable for the goals of this study.

5.3 Policy Implications

Understanding how place-based resources are distributed among eligible areas is important for several reasons. Concentrated poverty has increased since 2000, and more than 70 million people now live in a census tract in which at least 20 percent of their neighbors are poor (P. A. Jargowsky, 2013). Unfortunately, the resources available for addressing this widespread problem are limited, so it is critical that programs like NMTC and LIHTC target places where they can have the biggest possible impact on local conditions. This raises the fundamental question of whether priority should be on moderately distressed places that are well-positioned to leverage NMTC- or LIHTC-investment as a catalyst for sustained private investment and revitalization or on places struggling with extreme levels of socioeconomic distress with the greatest overall need for a variety of sustained policy interventions. This research supports the unsurprising argument that the market actors that utilize these programs prioritize the former. However, the relatively low levels of NMTC and LIHTC investment in high-density neighborhood types that were only moderately distressed suggests that both programs have in place effective combinations of incentives and disincentives for moderating the motivation for developers to seek out the most stable and urbanized eligible locations, and make investments into a much wider range of distressed places.

From an evaluation perspective, the deep parallels in the treatment selection processes guiding NMTC and LIHTC suggests the need for more integrated and nuanced assessments of these types of programs. This study did not provide a conclusive answer to the question of whether LIHTC investment into poor neighborhoods improves local conditions or mainly serves to reinforce existing patterns of concentrated poverty. However, it did find that the addition of LIHTC activity in a census tract generally had a modest negative impact on indicators used to judge the effectiveness of these sorts of programs. Thus, the revitalizing effects of NMTC and the poverty-concentrating effects of LIHTC are likely to cancel each other out, at least partially, unless explicit steps are taken to account for their underlying similarities.

However, NMTC and LIHTC are just the tip of the place-based iceberg. There are many other federal, state, and local programs that, just like NMTC and LIHTC, harness market forces to address the market failures that have left many distressed places chronically cut off from critical financial resources. Thus, controlling for the presence of LIHTC activity when estimating the effects of NMTC investment, and vice versa, is a first step towards research designs that better consider the underlying neighborhood factors that are likely to attract place-based investment from multiple sources beyond these two programs.

Recognizing the difficulty of fully representing the complicated policy environment in poor neighborhoods, a more nuanced take on the concept of success is also warranted. For all their similarities, NMTC and LIHTC address different problems. It may not be reasonable to expect that the economic and community development focus of NMTC would produce the same kinds of neighborhood changes as LIHTC, which addresses the undersupply of quality affordable housing options for poor residents, even if both programs are functioning as intended. Therefore, the socioeconomic change variables used in this and similar studies as indicators of program impact should be interpreted with the understanding that defining success in the context of a problem as complex and multifaceted as neighborhood poverty involves several considerations, not all of which are easy to measure.

5.4 Directions for Future Research

The research carried out in this dissertation provides numerous jumping off points for further exploring the various contexts of neighborhood poverty, the problems arising in these areas that place-based programs like NMTC and LIHTC are intended to address, the relationships between different sources of place-based investment, and methods for evaluating place-based programs that integrate multiple investment sources into a single analytical framework. Perhaps the most natural first step forward from here would be to reconsider the questions driving this research in the various poverty contexts this study revealed. For instance, within each neighborhood type, does it still hold true that the urbanization dimension is the common thread that explains NMTC investment, LIHTC investment, and socioeconomic ascent? Or are there other neighborhood attributes or dimensions that are better at explaining these processes in some neighborhood types? Along the same lines, are there variations in the effects of NMTC and LIHTC investment across neighborhood types? Are there some poverty contexts in which the revitalizing forces of LIHTC-subsidized development outweigh the poverty-concentrating forces? Similarly, are the socioeconomic benefits of NMTC investment relatively evenly distributed across neighborhood types, or are they concentrated within just a few select types of poor census tracts?

APPENDIX

Comparison of Group Means Before and After Matching: NMTC and LIHTC Investment Versus NMTC Investment Alone

	Before Matching		After Matching	
Variable Name	Both	NMTC	Both	NMTC
n	172	568	160	160
Income	$39,635	$40,944	$39,558	$39,534
Tract/Metro Income	52.22	55.49	51.99	52.69
Poverty Rate	30.14	28.39	30.16	31.20
Unemployment Rate	12.77	11.96	12.78	12.54
Pct. Females in Labor Force	50.64	52.58	50.50	51.43
Pct. White	35.10	36.68	33.81	39.02
Pct. Black	27.78	32.11	27.35	24.15
Pct. Hispanic	28.64	24.75	30.10	28.92
Pct. Asian	6.35	4.27	6.59	5.53
Pct. Foreign born	20.69	17.91	21.57	21.62
Pct. H.S. Diploma or Less	61.77	63.97	62.70	64.70
Pct. Bachelors or More	14.79	13.57	14.11	14.45
Pct. Households Female-headed	26.66	26.36	26.82	25.69
Tract/Metro Pop. Density	143	152	147	155
Pct. Housing Owner-occupied	29.43	35.61	30.49	30.05
Pct. Housing Multi-unit	62.87	54.29	61.40	60.81
Pct. Housing Vacant	9.91	10.50	9.57	8.94
Tract/Metro Median Home Value	73.41	66.51	68.07	65.18
Urbanization Index Score	0.59	0.28	0.54	0.52
Tract/Metro Median Home Value	0.73	0.67	0.68	0.65

Comparison of Group Means Before and After Matching: NMTC and LIHTC Investment Versus LIHTC Investment Alone

Variable Name	Before Matching Both	Before Matching LIHTC	After Matching Both	After Matching LIHTC
n	172	1662	163	163
Income	$39,635	$40,210	$39,595	$39,137
Tract/Metro Income	52.22	55.32	52.12	51.34
Poverty Rate	30.14	29.16	29.91	30.11
Unemployment Rate	12.77	12.59	12.68	12.99
Pct. Females in Labor Force	50.64	51.44	50.60	51.36
Pct. White	35.10	30.37	34.65	31.75
Pct. Black	27.78	36.97	27.41	28.99
Pct. Hispanic	28.64	26.51	29.33	31.88
Pct. Asian	6.35	4.66	6.44	5.71
Pct. Foreign born	20.69	18.77	21.16	22.89
Pct. H.S. Diploma or Less	61.77	64.90	62.39	64.52
Pct. Bachelors or More	14.79	11.97	14.42	12.67
Pct. Households Female-headed	26.66	28.07	26.61	28.64
Tract/Metro Pop. Density	143	168	145	167
Pct. Housing Owner-occupied	29.43	37.80	30.47	28.29
Pct. Housing Multi-unit	62.87	50.06	61.51	62.38
Pct. Housing Vacant	9.91	9.80	9.88	9.10
Tract/Metro Median Home Value	73.41	64.44	68.42	68.51
Urbanization Index Score	0.59	0.23	0.53	0.63

Comparison of Group Means Before and After Matching: NMTC and LIHTC Investment Versus No Treatment

Variable Name	Before Matching Both	Before Matching Neither	After Matching Both	After Matching Neither
n	172	12327	169	169
Income	$39,635	$43,742	$39,618	$38,828
Tract/Metro Income	52.22	60.44	52.22	51.05
Poverty Rate	30.14	25.24	30.24	31.80
Unemployment Rate	12.77	10.61	12.70	12.95
Pct. Females in Labor Force	50.64	52.62	50.67	52.68
Pct. White	35.10	36.43	34.65	35.15
Pct. Black	27.78	30.70	27.71	25.88
Pct. Hispanic	28.64	26.77	29.08	31.29
Pct. Asian	6.35	4.34	6.41	5.90
Pct. Foreign born	20.69	19.40	20.95	24.49
Pct. H.S. Diploma or Less	61.77	63.64	62.05	63.74
Pct. Bachelors or More	14.79	13.15	14.60	14.49
Pct. Households Female-headed	26.66	23.64	26.69	26.33
Tract/Metro Pop. Density	143	166	143	152
Pct. Housing Owner-occupied	29.43	45.25	29.79	30.25
Pct. Housing Multi-unit	62.87	43.67	62.31	62.54
Pct. Housing Vacant	9.91	9.25	9.91	8.95
Tract/Metro Median Home Value	0.73	0.66	0.72	0.70
Urbanization Index Score	0.59	-0.07	0.57	0.61

Comparison of Group Means Before and After Matching: NMTC Investment Versus LIHTC Investment

Variable Name	Before Matching NMTC	Before Matching LIHTC	After Matching NMTC	After Matching LIHTC
n	568	1662	552	552
Income	$40,944	$40,210	$40,817	$39,233
Tract/Metro Income	55.49	55.32	55.30	54.33
Poverty Rate	28.39	29.16	28.34	30.10
Unemployment Rate	11.96	12.59	11.92	12.75
Pct. Females in Labor Force	52.58	51.44	52.58	50.60
Pct. White	36.68	30.37	36.03	33.13
Pct. Black	32.11	36.97	32.38	35.40
Pct. Hispanic	24.75	26.51	25.12	25.39
Pct. Asian	4.27	4.66	4.31	4.67
Pct. Foreign born	17.91	18.77	18.12	19.00
Pct. H.S. Diploma or Less	63.97	64.90	64.12	64.77
Pct. Bachelors or More	13.57	11.97	13.47	12.43
Pct. Households Female-headed	26.36	28.07	26.50	28.17
Tract/Metro Pop. Density	152	168	154	161
Pct. Housing Owner-occupied	35.61	37.80	36.01	34.76
Pct. Housing Multi-unit	54.29	50.06	53.75	53.94
Pct. Housing Vacant	10.50	9.80	10.41	10.06
Tract/Metro Median Home Value	0.67	0.64	0.65	0.66
Urbanization Index Score	0.28	0.23	0.26	0.33

Comparison of Group Means Before and After Matching: NMTC Investment Versus No Treatment

Variable Name	Before Matching NMTC	Before Matching Neither	After Matching NMTC	After Matching Neither
n	568	12327	564	564
Income	$40,944	$43,742	$40,830	$40,770
Tract/Metro Income	55.49	60.44	55.34	55.00
Poverty Rate	28.39	25.24	28.39	28.53
Unemployment Rate	11.96	10.61	11.94	11.87
Pct. Females in Labor Force	52.58	52.62	52.57	51.94
Pct. White	36.68	36.43	36.58	35.08
Pct. Black	32.11	30.70	32.18	33.14
Pct. Hispanic	24.75	26.77	24.79	25.73
Pct. Asian	4.27	4.34	4.27	4.36
Pct. Foreign born	17.91	19.40	17.93	19.68
Pct. H.S. Diploma or Less	63.97	63.64	64.01	63.38
Pct. Bachelors or More	13.57	13.15	13.53	13.69
Pct. Households Female-headed	26.36	23.64	26.46	26.64
Tract/Metro Pop. Density	152	166	153	156
Pct. Housing Owner-occupied	35.61	45.25	35.82	34.90
Pct. Housing Multi-unit	54.29	43.67	54.01	55.43
Pct. Housing Vacant	10.50	9.25	10.46	9.93
Tract/Metro Median Home Value	0.67	0.66	0.66	0.66
Urbanization Index Score	0.28	-0.07	0.27	0.32
Tract/Metro Median Home Value	0.02	-0.02	0.01	0.01

Comparison of Group Means Before and After Matching: LIHTC Investment Versus No Treatment

	Before Matching		After Matching	
Variable Name	LIHTC	Neither	LIHTC	Neither
n	1662	12327	1660	1660
Income	$40,210	$43,742	$40,221	$40,170
Tract/Metro Income	55.32	60.44	55.32	55.49
Poverty Rate	29.16	25.24	29.14	29.17
Unemployment Rate	12.59	10.61	12.59	12.39
Pct. Females in Labor Force	51.44	52.62	51.44	51.79
Pct. White	30.37	36.43	30.35	29.21
Pct. Black	36.97	30.70	37.01	37.10
Pct. Hispanic	26.51	26.77	26.53	28.04
Pct. Asian	4.66	4.34	4.63	4.12
Pct. Foreign born	18.77	19.40	18.76	19.16
Pct. H.S. Diploma or Less	64.90	63.64	64.92	65.16
Pct. Bachelors or More	11.97	13.15	11.96	12.13
Pct. Households Female-headed	28.07	23.64	28.06	27.51
Tract/Metro Pop. Density	168	166	168	167
Pct. Housing Owner-occupied	37.80	45.25	37.83	38.40
Pct. Housing Multi-unit	50.06	43.67	50.09	48.55
Pct. Housing Vacant	9.80	9.25	9.81	9.80
Tract/Metro Median Home Value	0.64	0.66	0.64	0.64
Urbanization Index Score	0.23	-0.07	0.23	0.20

REFERENCES

Abravanel, M. D. (2010). Evaluating community and economic development programs: A literature review to inform evaluation of the New Markets Tax Credit Program.

Abravanel, M. D., Pindus, N. M., Theodos, B., Bertumen, K., Brash, R., & McDade, Z. (2013). NEW MARKETS TAX CREDIT (NMTC) PROGRAM EVALUATION. *Contract*.

Arnott, R. (1998). Economic theory and the spatial mismatch hypothesis. *Urban studies, 35*(7), 1171-1185.

Baltimore City's 2014 Housing Market Typology. (2015). Baltimore Retrieved from http://planning.baltimorecity.gov/sites/default/files/hmtdata.pdf.

Barr, M. S. (2002). Access to Financial Services in the 21st Century: Five Opportunities for the Bush Administration and the 107th Congress. *Notre Dame JL Ethics & Pub. Pol'y, 16*, 447.

Baum-Snow, N., & Marion, J. (2009). The effects of low income housing tax credit developments on neighborhoods. *Journal of Public Economics, 93*(5), 654-666.

Black, D., & Caputo, S. (2013). *New Markets Tax Credits: Unlocking Investment Potential*. Retrieved from Washington, D.C.: http://www.occ.gov/topics/community-affairs/publications/insights/insights-new-markets-tax-credits.pdf

Bokath, M. (2010). Take the Money and Run: A Case for Benchmarking in the New Markets Tax Credit Program. *Cal. WL Rev., 47*, 411.

Boswell, L. K. (2011). *Do Neighborhood Housing Market Typologies Matter? Measuring The Impact Of The Home Partnership Investment Program In Baltimore, Maryland.*

Brostek, M. (2009). *New Markets Tax Credit: Minority Entities are Less Successful in Obtaining Awards Than Non-Minority Entities*: DIANE Publishing.

Busso, M., Gregory, J., & Kline, P. M. (2010). *Assessing the incidence and efficiency of a prominent place based policy*.

Burgess, E. W. (2008). The growth of the city: an introduction to a research project Urban ecology (pp. 71-78): Springer.

CDFI Fund. (2012). *New Markets Tax Credit Fact Sheet*. Retrieved from http://www.cdfifund.gov/docs/factsheets/CDFI_NMTC.pdf

Clay, P. L. (1979). *Neighborhood renewal: middle-class resettlement and incumbent upgrading in American neighborhoods*: Free Press.

Cortright, J., & Mahmoudi, D. (2014). Lost in place: Why the persistence and spread of concentrated poverty--not gentrification--is our biggest urban challenge. *City Observatory (www. cityobservatory. org)*.

Coutts, A., & Kawachi, I. (2006). The urban social environment and its effects on health. *Cities and the health of the public,* 49-60.

Crane, R., & Manville, M. (2008). People or place? Revisiting the who versus the where of urban development. *Land Lines, 20*(3), 2-7.

Coulton, C. J. (2014). Using Data to Understand Residential Mobility and Neighborhood Change. In N. Cytron, K. Pettit, G. T. Kingsley, D. J. Erickson, & E. Seidman (Eds.), What Counts: Harnessing Data for America's Communities (pp. 261-270): Federal Reserve Bank of San Francisco.

Cummings, J. L., & DiPasquale, D. (1999). The Low-Income Housing Tax Credit An Analysis of the First Ten Years. *Housing Policy Debate, 10*(2), 251-307.

Davidson, N. M. (2009). Reconciling people and place in housing and community development policy. *Geo. J. on Poverty L. & Pol'y, 16*, 1.

de Souza Briggs, X., Popkin, S. J., & Goering, J. (2010). *Moving to opportunity: The story of an American experiment to fight ghetto poverty*: Oxford University Press.

Delmelle, E. C. (2015). Five decades of neighborhood classifications and their transitions: A comparison of four US cities, 1970–2010. *Applied Geography, 57*, 1-11.

Delmelle, E. C. (2017). Differentiating pathways of neighborhood change in 50 US metropolitan areas. *Environment and Planning A*, 0308518X17722564.

Desai, M. A., Dharmapala, D., & Singhal, M. (2008). *Investable tax credits: the case of the low income housing tax credit*: National Bureau of Economic Research.

Edelman, P. (2012). Our History with Concentrated Poverty.

Ellen, I. G., O'Regan, K., & Voicu, I. (2009). Siting, spillovers, and segregation: A reexamination of the Low Income Housing Tax Credit program. *Housing Markets and the Economy: Risk, Regulation, Policy; Essays in Honor of Karl Case*, 233-267.

Erickson, D. J., Galloway, I., & Cytron, N. (2012). Routinizing the Extraordinary. In N. O. Andrews & D. J. Erickson (Eds.), *Investing in What Works for America's Communities: Essays on People, Places & Purpose*. San Francisco: Federal Reserve Bank of San Francisco

Eriksen, M. D., Rosenthal, S. S., DiPasquale, G. E., Kubik, J., Olsen, E., Poethig, E., . . . Yinger, J. (2007). Crowd out, stigma, and the effect of place-based subsidized rental housing.

FFIEC. (2013). History of HMDA. Retrieved from http://www.ffiec.gov/hmda/history2.htm

Field, A. (2009). *Discovering statistics using SPSS*: Sage publications.

Forbes, J. (2006). Using economic development programs as tools for urban revitalization: A comparison of empowerment zones and new markets tax credits. *University of Illinois Law Review*(1), 177-203.

Fraley, C., & Raftery, A. E. (1998). How many clusters? Which clustering method? Answers via model-based cluster analysis. *The computer journal, 41*(8), 578-588.

Fraley, C., & Raftery, A. E. (2006). *MCLUST version 3: an R package for normal mixture modeling and model-based clustering*. Retrieved from

Freedman, M. (2012). Teaching new markets old tricks: The effects of subsidized investment on low-income neighborhoods. *Journal of Public Economics, 96*(11-12), 1000-1014. doi:10.1016/j.jpubeco.2012.07.006

Fund, C. (2017a). *NMTC Program 2017 Allocation Application*. Retrieved from https://www.cdfifund.gov/Documents/2017%20NMTC%20Allocation%20Application%20-%20For%20Public%20Release_May24.pdf.

Fund, C. (2017b). *NMTC Qualified Equity Investment Report*. Retrieved from https://www.cdfifund.gov/Documents/May%202017%20QEI%20Issuance%20Report.pdf

Galea, S., Freudenberg, N., & Vlahov, D. (2006). A framework for the study of urban health. *Cities and the Health of the Public. Vanderbilt University Press, Nashville, TN*, 3-18.

Galster, G. (2001). On the nature of neighbourhood. *Urban studies, 38*(12), 2111-2124.

Galster, G. (2012). The mechanism (s) of neighbourhood effects: Theory, evidence, and policy implications. In *Neighbourhood effects research: New perspectives* (pp. 23-56): Springer.

Galster, G., Tatian, P., & Accordino, J. (2006). Targeting investments for neighborhood revitalization. *Journal of the American Planning Association, 72*(4), 457-474.

Galster, G., Walker, C., Hayes, C., Boxall, P., & Johnson, J. (2004). Measuring the impact of Community Development Block Grant spending on urban neighborhoods. *Housing Policy Debate, 15*(4), 903-934.

Galvez, M. M. (2010). What Do We Know About Housing Choice Voucher Program Location Outcomes? *A review of recent literature. Washington, DC: The Urban Institute*.

Glaeser, E. L., & Gottlieb, J. D. (2008). *The economics of place-making policies*. Retrieved from

Gobillon, L., Selod, H., & Zenou, Y. (2007). The mechanisms of spatial mismatch. *Urban studies, 44*(12), 2401-2427.

Goldrick-Rab, S., Richardson, J., & Hernandez, A. (2017). *Hungry and Homeless in College: Results from a National Study of Basic Needs Insecurity in Higher Education*. Retrieved from http://wihopelab.com/publications/Hungry-and-Homeless-in-College-Report.pdf

Goldstein, I. (2011). Market Value Analysis: A Data-Based Approach to Understanding Urban Housing Markets. In M. H. Lambert, Jane (Ed.), *Putting Data to Work: Data-Driven Approaches to Strengthening Neighborhoods*: Board of Governors of the Federal Reserve System

Goldstein, I. (2012). Market value analysis: A data-based approach to understanding urban housing markets. *Putting Data to Work: Data-Driven Approaches to Strengthening Neighborhoods*, 49-60.

Gotham, K. F. (2000). Racialization and the state: the Housing Act of 1934 and the creation of the Federal Housing Administration. *Sociological Perspectives*, 291-317.

Greenberg, M. (1997). *The GI bill: The law that changed America*: Lickle Pub.

Greer, S. A. (1962). *The emerging city: Myth and reality*: Transaction Publishers.

Gurley-Calvez, T., Gilbert, T. J., Harper, K., Marples, D. J., & Daly, K. (2009). Do tax incentives affect investment? An analysis of the New Markets Tax Credit. *Public Finance Review, 37*(4), 371-398.

Hanlon, B. (2009). A typology of inner-ring suburbs: Class, race, and ethnicity in US Suburbia. *City & Community, 8*(3), 221-246.

Harger, K., & Ross, A. (2014). *Do Capital Tax Incentives Attract New Businesses? Evidence across Industries from the New Markets Tax Credit*. Retrieved from

Helms, A. C. (2003). Understanding gentrification: an empirical analysis of the determinants of urban housing renovation. *Journal of urban economics, 54*(3), 474-498.

Hill, L. E., & Johnson, H. P. (2011). *Unauthorized immigrants in California: Estimates for counties*: Public Policy Instit. of CA.

Ho, D. E., Imai, K., King, G., & Stuart, E. A. (2007). Matching as nonparametric preprocessing for reducing model dependence in parametric causal inference. *Political analysis, 15*(3), 199-236.

Horn, K. M., & O'Regan, K. M. (2011). The low income housing tax credit and racial segregation. *Housing Policy Debate, 21*(3), 443-473.

Hwang, J. (2016). Pioneers of gentrification: Transformation in global neighborhoods in urban America in the late twentieth century. *Demography, 53*(1), 189-213.

Hwang, J., & Sampson, R. J. (2014). Divergent pathways of gentrification: Racial inequality and the social order of renewal in Chicago neighborhoods. *American Sociological Review, 79*(4), 726-751.

IRS. (2010). *New Markets Tax Credit*. Retrieved from s

Jakubowski, M. (2014). Latent variables and propensity score matching: a simulation study with application to data from the Programme for International Student Assessment in Poland. *Empirical Economics*, 1-39.

Jargowsky, P., & Bane, M. J. (1991). Ghetto poverty in the United States. *The urban underclass, 235*, 251-252.

Jargowsky, P. A. (2009). Immigrants and neighbourhoods of concentrated poverty: assimilation or stagnation? *Journal of Ethnic and Migration Studies, 35*(7), 1129-1151.

Jargowsky, P. A. (2013). *Concentration of Poverty in the New Millennium*.

Johnson, M. (2014). Poverty Deconcentration Priorities in Low-Income Housing Policy: A Content Analysis of Low-Income Housing Tax Credit (LIHTC) Qualified Allocation Plans.

Jun, K.-N., & Musso, J. (2013). Participatory Governance and the Spatial Representation of Neighborhood Issues. *Urban Affairs Review, 49*(1), 71-110. doi:10.1177/1078087412453704

Kasarda, J. D. (1993). Inner-city concentrated poverty and neighborhood distress: 1970 to 1990. *Housing Policy Debate, 4*(3), 253-302.

Kingsley, G. T. (2007). Concentrated poverty: Dynamics of change.

Kneebone, E., & Berube, A. (2013). *Confronting suburban poverty in America*: Brookings Institution Press.

Kraybill, D., & Kilkenny, M. (2003). *Economic rationales for and against place-based policies.* Paper presented at the AAEA-RSS Annual Meeting, Montreal, July.

Ladd, H. F. (1994). Spatially targeted economic development strategies: do they work? *Cityscape, 1*(1), 193-218.

Lechner, M. (2001). *Identification and estimation of causal effects of multiple treatments under the conditional independence assumption*: Springer.

Lechner, M. (2002). Program heterogeneity and propensity score matching: An application to the evaluation of active labor market policies. *Review of Economics and Statistics, 84*(2), 205-220.

Levy, J. M. (2009). *Contemporary Urban Planning* (8th ed.). Upper Saddle River, New Jersey: Prentice Hall.

Massey, D. S. (1993). *American apartheid: Segregation and the making of the underclass*: Harvard University Press.

Massey, D. S., & Denton, N. A. (1993). *American apartheid: Segregation and the making of the underclass*: Harvard University Press.

Massey, D. S., Goldring, L., & Durand, J. (1994). Continuities in transnational migration: An analysis of nineteen Mexican communities. *American journal of Sociology, 99*(6), 1492-1533.

McHugh, K. E. (1987). Black migration reversal in the United States. *Geographical Review*, 171-182.

Mikelbank, B. A. (2004). A typology of US suburban places. *Housing Policy Debate, 15*(4), 935-964.

Neumark, D., & Simpson, H. (2014). *Place-based policies*. Retrieved from

NMTCC. (2012). *The New Markets Tax Credit: Progress Report 2012*. Retrieved from Washington, D.C.: http://nmtccoalition.org/wp-content/uploads/NMTC-2012-Progress-Report.pdf

Oakley, D., & Tsao, H.-s. (2007). Socioeconomic gains and spillover effects of geographically targeted initiatives to combat economic distress: An examination of Chicago's Empowerment Zone. *Cities, 24*(1), 43-59.

Orfield, M. (2011). *Metropolitics: A regional agenda for community and stability*: Brookings Institution Press.

Owens, A. (2012). Neighborhoods on the Rise: A Typology of Neighborhoods Experiencing Socioeconomic Ascent. *City & Community, 11*(4), 345-369. doi:10.1111/j.1540-6040.2012.01412.x

Partridge, M. D., & Rickman, D. S. (2006). *The geography of American poverty: Is there a need for place-based policies?* : WE Upjohn Institute.

Peters, D. J. (2009). Typology of American poverty. *International Regional Science Review, 32*(1), 19-39.

Pett, M. A., Lackey, N. R., & Sullivan, J. J. (2003). *Making sense of factor analysis: The use of factor analysis for instrument development in health care research*: Sage.

Popkin, S. J. (2004). A decade of HOPE VI: Research findings and policy challenges.

Porter, M. E. (1997). New strategies for inner-city economic development. *Economic Development Quarterly, 11*(1), 11-27.

Poverty Areas. (1995). *U.S. Census Bureau Statistical Brief*. Retrieved from https://www.census.gov/population/socdemo/statbriefs/povarea.html

Puentes, R., & Orfield, M. (2002). Valuing America's first suburbs: A policy agenda for older suburbs in the Midwest.

Reid, C. (2011). The neighborhood stabilization program: Strategically targeting public investments. *Community Investments, 23*(1), 23-33.

Reserve, F. (2014). Community Reinvestment Act. Retrieved from http://www.federalreserve.gov/communitydev/cra_about.htm

Richter, F., Sniderman, M. S., Klesta, M., & Manzo, F. (2013). Low-Income-Rental-Housing Programs in the Fourth District.

Ricketts, E. R., & Sawhill, I. V. (1988). Defining and measuring the underclass. *Journal of Policy Analysis and Management, 7*(2), 316-325.

Rohe, W. M., & Stewart, L. S. (1996). Homeownership and neighborhood stability. Housing Policy Debate, 7(1), 37-81.

Sallis, J. F., Cervero, R. B., Ascher, W., Henderson, K. A., Kraft, M. K., & Kerr, J. (2006). An ecological approach to creating active living communities. *Annu. Rev. Public Health, 27*, 297-322.

Sampson, R. J. (2012). *Great American city: Chicago and the enduring neighborhood effect*: University of Chicago Press.

Sampson, R. J., & Wilson, W. J. (1995). Toward a theory of race, crime, and urban inequality. *Race, crime, and justice: A reader*, 177-190.

Schill, M. H., & Wachter, S. M. (1995). The spatial bias of federal housing law and policy: Concentrated poverty in urban America. *University of Pennsylvania Law Review*, 1285-1342.

Schwirian, K. P. (1983). Models of neighborhood change. *Annual Review of Sociology, 9*(1), 83-102.

Shevky, E., & Bell, W. (1955). Social area analysis; theory, illustrative application and computational procedures.

Swack, M., Hangen, E., & Northrup, J. (2015). CDFIs Stepping into the Breach: An Impact Evaluation—Summary Report.

Teitz, M. B., & Chapple, K. (1998). The causes of inner-city poverty: Eight hypotheses in search of reality. *Cityscape*, 33-70.

Trochim, W. M., & Donnelly, J. P. (2001). Research methods knowledge base.

U.S. Department of Housing and Urban Development. (2014). Allocating Housing Tax Credits. Retrieved from http://portal.hud.gov/hudportal/HUD?src=/program_offices/comm_planning/affordablehousing/training/web/lihtc/basics/allocating

Van Criekingen, M., & Decroly, J.-M. (2003). Revisiting the diversity of gentrification: neighbourhood renewal processes in Brussels and Montreal. *Urban studies, 40*(12), 2451-2468.

Von Hoffman, A. (2012). The past, present, and future of community development in the United States. In N. O. Andrews & D. J. Erickson (Eds.), *Investing in What Works for America's Communities: Essays on People, Places & Purpose* (pp. 419). San Francisco: Federal Reserve Bank of San Francisco

Whisenant, A. (2014). *HUD Releases Proposed FY2015 Budget*. (HUD No. 14-019). Washington, D.C. Retrieved from http://portal.hud.gov/hudportal/HUD?src=/press/press_releases_media_advisories/2014/HUDNo.14-019.

White, J. R. (1997). *Opportunities to Improve Oversight of the Low-Income Housing Program*. (GAO/T-GGD/RCED-97-149). Washington, D.C.

Williamson, A. R., Smith, M. T., & Strambi-Kramer, M. (2009). Housing choice vouchers, the low-income housing tax credit, and the federal poverty deconcentration goal. *Urban Affairs Review, 45*(1), 119-132.

Wilson, W. J. (1978). The declining significance of race. *Society, 15*(5), 11-11.

Wilson, W. J. (2010). The Obama administration's proposals to address concentrated urban poverty. *City & Community, 9*(1), 41-49.

Wilson, W. J. (2011). *When work disappears: The world of the new urban poor*: Random House LLC.

Wilson, W. J. (2012). *The truly disadvantaged: The inner city, the underclass, and public policy*: University of Chicago Press.